2

AN ANALYSIS OF THE AIR FORCE LOGISTICS COMMAND (AFLC) FORECASTING METHOD FOR PREDICTING SECOND DESTINATION TRANSPORTATION (SDT)

THESIS

Stephen L. Strom
Captain, USAF

AFIT/GLM/LSM/89S-59

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY
AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

2

AFIT/GLM/LSM/89S-59

AN ANALYSIS OF THE AIR FORCE
LOGISTICS COMMAND (AFLC) FORECASTING
METHOD FOR PREDICTING SECOND
DESTINATION TRANSPORTATION (SDT)

THESIS

Stephen L. Strom
Captain, USAF

AFIT/GLM/LSM/89S-59

Approved for public release; distribution unlimited

The contents of the document are technically accurate, and no sensitive items, detrimental ideas, or deleterious information is contained therein. Furthermore, the views expressed in the document are those of the author and do not necessarily reflect the views of the School of Systems and Logistics, the Air University, the United States Air Force, or the Department of Defense.

AFIT/GLM/LSM/89S-59

AN ANALYSIS OF THE AIR FORCE LOGISTICS COMMAND (AFLC) FORECASTING METHOD FOR PREDICTING SECOND DESTINATION TRANSPORTATION (SDT)

THESIS

Presented to the Faculty of the School of Systems
and Logistics of the Air Force Institute of Technology
Air University
In Partial Fulfillment of the
Requirements for the Degree of
Master of Science in Logistics Management

Stephen L. Strom, B.S.
Captain, USAF

September 1989

Preface

The purpose of this research twofold. First, an attempt was made to validate the current forecasting method utilized by HQ AFLC/DSXR to predict SDT tonnage. Secondly, if this method was determined to be statistically invalid, an effort was made to develop a Box-Jenkins time series forecasting model that would produce more accurate and reliable results.

The current method employed by HQ AFLC/DSXR was, in fact, determined to be statistically invalid during the course of this research. Therefore, an attempt was made to develop a Box-Jenkins model that would offer more accurate results. Although a significantly more accurate model was not developed during this research, the need for developing such a model was given more urgency by the fact that the model currently used is invalid.

This research would not have been possible without the assistance and knowledge of Mr. George T. Menker and his staff at HQ AFLC/DSXR. I am also deeply indebted to my advisor and friend Lt Col Robert E. Trempe for his technical knowledge and patience in assisting me with this thesis. Finally, I wish to thank my wife Paula for her caring and undying patience as I struggled through this research and the entire AFIT graduate program. Without her support and the brightly shining face of my daughter Allison, this research would have been much harder.

Stephen L. Strom

Table of Contents

Page

List of Tables

List of Figures

AFIT/GT/LSM/89S-59

Abstract

This research was conducted to analyze the Air Force Logistics Command (AFLC) forecasting method for predicting Second Destination Transportation (SDT) tonnage with the regional flying hour program. This thesis had two main objectives: (1) validate the current forecasting method used for computing tonnage estimates to derive SDT budget requests, and (2) if the current method's validity was not supported, develop a new forecasting model, using the same input data, that would produce more accurate and reliable tonnage estimates.

Analyzing graphs of the four different data sets researched in this thesis and then conducting a statistical test on the flying hour parameter for each set, it was determined that the current method employed to forecast SDT tonnage was statistically invalid for two of the four sets. This determination was made due to the fact that the flying hour parameter changed during the iterative regression process used. This change implied that SDT tonnage and flying hours were not linearly related.

Box-Jenkins (BJ) time series forecasting models for each data set were built and provided accurate and valid forecasts. For the MAC SDT time series, the BJ models were more accurate than the current method. The BJ models for

the MSC SDT time series, although marginally less accurate than the current method, were valid, whereas the current method for these two series was statistically invalid.

This research emphasized the need for an accurate model and an increase in the size of the data base used for forecasting. It was also noted that forecasting SDT tonnage requires continual analysis and updating to ensure the model being used is appropriate for the data being forecasted. Finally, in statistically invalidating the current model, this research has caused an immediate need for an accurate and valid model. Further research, particularly with econometric models, would prove beneficial.

AN ANALYSIS OF THE AIR FORCE LOGISTICS COMMAND (AFLC)

FORECASTING METHOD FOR PREDICTING SECOND

DESTINATION TRANSPORTATION (SDT)

I. Introduction

The Budget and Requirements Division, Directorate of Programs and Resources, Deputy Chief of Staff Distribution, Headquarters Air Force Logistics Command (HQ AFLC/DSXR), is tasked with estimation and submittal of the AFLC budget for Second Destination Transportation (SDT). These estimates are derived from forecasted tonnage requirements and are submitted to the Plans and Programs Division, Directorate of Transportation, Headquarters United States Air Force (HQ USAF/LETX), who, in turn, consolidates all SDT estimates throughout the Air Force into an overall service SDT budget requirement. The major consequence of AFLC/DSXR underestimating its SDT requirements is that by the end of the fiscal year, SDT funds will be depleted and cargo requiring SDT will be delayed in reaching final destinations. This is a costly consequence as evidenced by a 28 September 1987 letter from Brigadier General Richard D. Smith, Deputy Chief of Staff Materiel Management, Headquarters Air Force Logistics Command (HQ AFLC/MM), to the Assistant Secretary of the Air Force for Logistics.

The letter stated:

> As requested, the cost of an additional day of shipping time of recoverable spares is $50.8 million. With approximately 24 percent of the shipments overseas, we estimate the cost of one day additional time at ports is $12.2 million. These numbers show the magnitute of impact of MAC consolidation of shipments at ports and shortfalls in Second Destination Transportation funding

Another problem with continually under or overesimating is that higher echelons (i.e. HQ USAF/LETX) lose confidence in the method of forecasting. This latter problem has, at times, plagued AFLC/DSXR. Accurate forecasting of SDT requirements will ensure all SDT shipments reach destination, and higher echelons will be more apt to believe in these forecasts.

In researching this topic, SDT must be clearly defined. To thoroughly define SDT, the Air Force first defines First Destination Transportation (FDT) as the movement of property from the point of origin, normally a contractor or supplier, to the point where the material is initially received by the Air Force for use or storage for subsequent distribution in the supply system (5:124). SDT is this subsequent distribution and includes:

1. Port handling.

2. Overocean transportation.

3. Shipments to Air Logistics Centers (ALC's) or contractor depots.

4. Shipments between bases.

5. Shipments from bases to repair facilities or depots. (5:124; 13; 14:32)

Currently, AFLC/DSXR uses the following linear regression methodology for SDT budget forecasting. Developed in the mid-1970s, it proceeds as follows:

1. The 40 most recent quarters of historical tonnage and flying hour data are obtained, broken down by overseas geographical region. The tonnage is also subdivided by means of transport.

2. A series of linear regressions, beginning with the initial 40 quarters of data, are conducted using Equation (1).

$$Y = \beta_0 + \beta_1 X \tag{1}$$

where: Y = the dependent, or forecasted, variable, SDT tonnage
X = the independent variable, flying hours
β_0 = the Y-axis intercept
β_1 = the independent variable parameter value, also the slope of the regression line.

During each subsequent regression, the number of quarters of data is decreased by eliminating the oldest quarter of data. The final regression iteration uses the eight most recent quarters.

3. For each regression, the coefficient of correlation (R), standard deviation, and tonnage forecasts are computed.

4. The regression with the highest R value is chosen as the equation to use, and the resulting tonnage forecasts are utilized to compute the SDT budget estimates.

AFLC/DSXR also applies a smoothing technique to remove the random variation within the regression. After this application, the 4-step procedure above is repeated. The final choice between this latter technique and the technique initially discussed above is arbitrary. The guidelines for directing this choice are consistency of technique use over a period of time and thorough comparisons of the forecasts to the most recent historical tonnage (1:3-4; 12). In other words, the method selected for use as the forecasting tool should either consistently employ the nonsmoothing or smoothing technique. In addition, the forecasts should be compared to recent historical tonnage to ensure there is no unexplained change.

Flying hours, the independent variable in the regression, is defined as the total number of hours flown by Air Force aircraft assigned to a specific overseas geographical region to which each forecast applies as well as hours flown by transient aircraft bedded down in the region in excess of 60 days (12). These hours do not include those flown by the MAC aircraft hauling SDT to these regions.

The forecasted requirements are divided into five means of transport:

1. Military Airlift Command (MAC).

2. Military Sealift Command (MSC).

3. Military Traffic Management Command (MTMC), which includes port handling operations.

4. Logistics airlift (LOGAIR).

5. Government Bills of Lading (GBL's), which include commercial air and surface transportation (13; 14:32,34). These are the five predominant means of transport utilized in shipping SDT within the Air Force.

The Air Force flying hour program by overseas geographical area is used as the independent variable in forecasting future tonnage requirements, the dependent variable, for each means of transportation except LOGAIR (10:3; 12; 14:34). This functional relation is shown in Equation (1) above. These means of transport, with the exception of LOGAIR, support five overseas geographical areas (major commands): European (USAFE), Pacific (PACAF), Alaskan (AAC), Southern (USAFSO), and Northeastern (northern radar sites) (10:3; 12).

The forecasted tonnage and subsequent SDT budget estimates are computed separately by geographical region for the following reasons:

1. Costs of cargo movement to and within each region differ due to the weight of the shipment and the distance moved.

2. Flying hours for aircraft assigned to each region are projected by the major command (MAJCOM) associated with that region (10:4). Hence, several different combinations of SDT tonnage forecasts are computed.

Table 1 depicts AFLC tonnage and cost for each mean in FY 88.

Table 1

Tonnage and Cost by Means - Fiscal Year 1988 (13)

Means	Tonnage (000)	Cost (millions)
MAC	83,563 S/T*	$130
MSC	1,098,820 M/T**	68
MTMC	984,774 M/T	14
LOGAIR	65,675 S/T	76
GBL	189,545 S/T	43
TOTAL		$331

* A short ton (S/T) is equal to 2,000 pounds.

** A measurement ton (M/T) is equivalent to approximately 40 cubic feet. (20:838)

As noted in the Table 1, MAC and MSC shipments were allotted a total of $198 million, or 57 percent of AFLC's SDT funding.

The SDT cost by theater is also an important consideration in the budgeting process. This cost breakdown allows AFLC to determine where the majority of its SDT expenditures occur. Table 2 lists the percent of SDT funding by MAJCOM based on FY 89 figures.

Table 2

Percent of AFLC SDT Cost in FY 89 by MAJCOM (13)

MAJCOM	Percent of Cost
USAFE	37
CONUS	29
PACAF	25
Northern	3
USAFSO	3
AAC	2
Other	1

As shown in Table 2, SDT shipments to USAFE and PACAF account for 62 percent of AFLC's FY 89 SDT funding. Shipments to these same two theaters account for 87 percent of AFLC's SDT funding for overseas areas.

Specific Problem

An accurate and reliable forecasting method to predict SDT requirements is necessary to ensure proper budget submittals. A reliable forecasting method is free of random error; therefore, when forecasting with a reliable method, the forecasts will show little or no random error, or differences from the actual values (6:98). An accurate forecast refers to the ability of the method to predict future values. Accuracy is a comparative measurement and the method exhibiting the best accuracy measurement is usually selected for forecasting (11:567). Several methods for measuring forecast accuracy are discussed in Chapter II.

The current forecasting method utilized by AFLC/DSXR for computing tonnage estimates to derive future SDT budget requests was developed in the mid-1970s and has not been validated in recent years. Validation of this current method would support or fail to support its accuracy and reliability as a forecasting tool. In validating the model, evidence must be found and presented showing that the method forecasts what it is suppose to forecast. In addition, evidence must be presented supporting a causal relationship between the variables in the forecasting model (4:37; 6:94).

Justification

The SDT budget estimates derived from the forecasted tonnage requirements are submitted to the Plans and Programs Division, Directorate of Transportation, HQ USAF/LETX, who, in turn, consolidates all SDT estimates throughout the Air Force into a service SDT budget requirement (12). Recently, USAF/LETX expressed concern with respect to the effectiveness of the current forecasting method in predicting future tonnage requirements (18). This concern stems from the cutbacks in SDT as well as other transportation funding. As a result of the recent funding cuts throughout the armed services, it is more critical than ever to be able to predict, with a greater amount of accuracy, future tonnage and funding requirements. Accurate predictions are necessary to ensure SDT funding is available throughout the fiscal year. Table 3 lays out the actual SDT funding for AFLC over the past five fiscal years.

Table 3

AFLC SDT Funding (millions) (13)

FY	Requirement	Funding	Difference
85	$407	$407	$0
86	407	407	0
87	410	410	0
88	385	315	-70
89	460	387	-73

As noted in Table 3, AFLC's SDT Program has been funded at less than 100 percent over the past two fiscal years.

Scope

Since 87 percent of overseas SDT occurs within USAFE and PACAF by MAC and MSC movements, AFLC/DSXR believes that if the forecasts for these areas and transportation means are validated, its forecasting method is reliable and accurate (12). For this reason, the research for this thesis was limited to the examination of the forecasts for these two areas by these two means of transport. In addition, this research was limited to the use of flying hours by overseas geographical location (USAFE or PACAF) as the independent variable to predict the dependent variable, SDT tonnage. This latter limitation was made to offer AFLC/DSXR the best possible forecasting method for the data it currently uses, and also due to a lack of data for other possible independent variables.

Research Objectives

This research was conducted to assist in validating the forecasting method utilized by AFLC/DSXR to predict SDT tonnage. These forecasts must be accurate to ensure proper budget requests are submitted for approval. Therefore, the research objectives of this thesis were to:

1. Validate the current forecasting method used for computing tonnage estimates to derive future SDT budget requests.

2. If the current method's validity was not supported, develop a new forecasting model, using the same input data, that would produce more accurate and reliable tonnage estimates.

Research Hypothesis

The research, or null, hypothesis (H_0) for this thesis is that the forecasting method utilized by AFLC/DSXR to compute SDT tonnage estimates is an accurate and reliable predictor of future SDT budget requirements. The alternate hypothesis (H_A) is that the method used is not an accurate and reliable predictor.

In research, only two conditions (or states of nature) exist, these being the null hypothesis is true or it is false. In addition, only one of two possible decisions about these states of nature is made -- the null hypothesis is either accepted as true or it is rejected as false. The combination of these two conditions and two decisions leads to four possible situations. Two situations lead to correct decisions, while the remaining two result in erroneous decisions (6:352-353). See Figure 1.

Decision	Condition: H_0 - true	Condition: H_0 - false
Accept H_0	Correct Decision Confidence level probability = $1-\alpha$	Type II error probability = β
Reject H_0	Type I error Significance level probability = α	Correct Decision probability = $1-\beta$

Figure 1. Hypothesis Testing
Condition - Decision Matrix (6:353)

Type I error (α) occurs when a true hypothesis is rejected and Type II error (β) occurs when a false hypothesis is accepted (6:353).

In research, the problem with accepting the null hypothesis is that it cannot be proven, but only supported or not supported. One reason for this problem is that there always remains a possibility that statistics will not detect a difference between the null and alternate hypotheses when, in fact, there was a difference. Secondly, future results, using more powerful statistical tests or analyses with higher correlation between variables, cannot be known in advance (4:44).

Although the null hypothesis cannot be proved or disproved, decisions must be made as though the null hypothesis is true or false. Acceptance or rejection of the null hypothesis should therefore be based on the confidence estimated in relation to established standards (4:45).

Several factors must be considered when setting standards for this research. First the cost of implementing a new computer forecasting software package is of major concern. Along with a new system comes training, and this factor is not costless and must therefore be considered. Increased confidence in the forecasts by higher echelons is also a factor. The new method should be considered for possible implementation if it provides more accurate and reliable forecasts and higher echelons are more confident in the results.

For this research, the confidence level probability, or the probability of accepting the null hypothesis when it is true, was set at 95 percent. In other words, the probability of making a Type I error (α) was set at 5 percent. This probability and associated null hypothesis is considered "conservative." This conservativeness implies that if the null hypothesis is rejected as false, there is almost no chance that the null hypothesis was in fact true.

AFLC/DSXR, in reviewing this research, should select confidence level and Type I error probabilities that meet its concerns based on the factors it considers relevant. However, the confidence level and Type I probability error selected for this research provide adequate protection to AFLC/DSXR from incurring unnecessary switching costs while subjecting the current forecasting methodology to a rigorous test of its accuracy.

Plan of Analysis

The remaining chapters of this thesis are devoted to the actual development and implementation of the research. Chapter II is devoted to a review of the literature concerning the current forecasting method as well as the general topic of forecasting. Chapter III lays out the methodology used to conduct this research in pursuit of the objectives stated earlier. The results and analysis of this research are presented in Chapter IV. Finally, Chapter V is devoted to the findings and implications of this research.

II. Literature Review

This literature review is composed of three parts. The first section briefly explains the concept of forecasting and offers an outline of forecasting methods as well as a group of methods for measuring forecast accuracy. The second part details the current forecasting method utilized by AFLC/DSXR in forecasting future SDT tonnage. Finally, in the third section, previous reports and studies conducted on AFLC/DSXR's current forecasting method are reviewed and analyzed.

Forecasting

Forecasting is conducted for two main purposes: extrapolation and intervention analysis. Extrapolation is predicting how future events will develop based on past events. Intervention analysis predicts the effect of management decisions or policy changes, and if an effective change does occur, assists in determining the direction and magnitude of the change (2:12.18-12.19).

Forecasting was conducted in this thesis for the purpose of extrapolation. Predictions of future SDT tonnage are needed to ensure proper budget submittals. Caution must be exercised with regard to extrapolating past the scope of the data used to construct the model. However, in order to provide a forecast of the future, extrapolation must be conducted. Accuracy in forecasting, therefore, is essential, and without it, resultant decisions based on these forecasts will be erroneous.

Typology of Forecasting. There are many different categorizations, or typologies, of forecasting methods; however, most typologies include the same methods and only the groupings differ. There are five main categories of forecasting methods including:

1. Subjective.
2. Ad hoc.
3. Causal or structural.
4. Deterministic.
5. Time series.

Subjective. Subjective forecasting methods are heavily reliant on the opinions of the forecaster and involve techniques such as an educated guess, engineering judgment, or Delphi. Subjective models are intuitive and are the most commonly used forecasting technique. Reasons for using a subjective approach are short response times, costs of using a more sophisticated technique, and lack of historical data. The main characteristic of subjective forecasts is that they cannot be replicated due to the lack of an actual "model" (2:12.7-12.8; 3).

Ad Hoc. Ad hoc forecasting methods are based primarily on past history and work well in areas of apparent stability. Ad hoc models include, but are not limited to:

1. Simple average.

2. Simple moving average.

3. Weighted moving average.

4. Exponential smoothing.

5. Holt's Two-Parameter Model.

6. Winter's Three-Parameter Model.

The simple average is accurate when there is stability, or stationarity, within the data accompanied by little variation. Stationarity implies there is no trend in the data or that the mean of the data remains constant. The simple moving average, or moving average, eliminates the need to store large amounts of data necessary to use the simple average; however, valuable information maybe lost if old, but informative, data are excluded. The weighted moving average allows the forecast to give differing weights to different observations. This alleviates the problem in using the moving average where all observations are given equal weights. Exponential smoothing is useful if the data are stationary. Holt's Two-Parameter Model works well on data with both stationary and trend components. A trend occurs when the variance of the data remains the same, but the mean changes up or down. Finally, if the data exhibit a seasonal component as well as stationary and trend components, the Winter's Three-Parameter Model works best. Seasonality is defined as periodicity within the data and may occur every 12 periods within monthly data or every four periods within quarterly data (2:12.8-12.10,12.16; 3; 11:14-16).

Causal. Causal, or structural, forecasting methods are often referred to as econometric models. The forecast is a set of functions based on assumed or theoretical causal relationships in the data. Simple linear and multiple regression models are of this type. An example of a simple linear regression model is in Equation (2). Simple linear regression is a special case of multiple regression in that only one independent variable is used.

$$Y = \beta_0 + \beta_1 X + e \tag{2}$$

where: Y = a series of historical values of a dependent variable
X = a corresponding, or causal, series values of an independent variable
β_0 = the Y-axis intercept
β_1 = independent variable parameter value; slope of the line
e = error term.

A multiple regression model example is in Equation (3).

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + e \tag{3}$$

where: Y_i = dependent variable observation
X_{ki} = the observed value of the independent variable
β_k = the independent variable parameter value
e = error term.

AFLC/DSXR's current method is similar to equation (2) with Y equal to SDT tonnage and X equal to flying hours. In causal model development, the forecaster must ensure all pertinent variables are included and nonexplanatory variables are excluded (2:12.12-12.14; 3; 9:10-11).

Two problems involved with regression are heteroscedasticity and autocorrelation. Heteroscedasticity, or unequal variances within the data, does not normally occur in time series studies. This is due to the likelihood of the changes in the dependent variable and the changes in any number of the independent variables being of the same magnitude. In regression, however, variances of the error term are not used to prove the absence of bias. Therefore, the problem encountered in regression when heteroscedasticity is present is that biased estimates of parameter variances are used thus the statistical tests and confidence intervals used are incorrect (17:141-142).

Autocorrelation, or serial correlation, occurs when errors associated with a given observation carry over into other periods. Generally, autocorrelation does not affect the unbiasedness of regression model estimators, but does affect the estimators' efficiency. Under positive autocorrelation, the parameter estimates are concluded to be more precise than they actually are, and this leads to the tendency to reject the null hypothesis when, in fact, it is true (17:152-153).

Deterministic. Deterministic forecasting methods make the dependent, or observed, variable a function of time and are of the form in Equation (4).

$$Y_t = f(t) \qquad (4)$$

where: $f(t)$ = a function of time.

This type of model forecasts the future behavior of a time series based on past behavior. Deterministic implies that reference is not made to the sources or causes of randomness within the data (17:473). As in causal models, heteroscedasticity and autocorrelation may present problems and affect the ultimate accuracy of the model.

Time Series. Time series models identify patterns in the history of a variable and use the information gathered to predict future values of that same variable. These models are used when there is no knowledge about the causal relationships affecting the variable being forecasted (17:470-471). Most time series methods assume the following characteristics:

1. The time period at which each data value is measured is of equal length (i.e. years, quarters, months).

2. The data values are arranged in time sequence from the earliest to latest time period, and there are no missing values.

3. The process and method of measurement are consistent over time (9:5).

Time series forecasting models follow one of two approaches: self-projecting or cause-and-effect (9:9).

Self-projecting, or univariate, methods are based on the history of the times series, and range in sophistication from moving averages to Box-Jenkins. These methods are useful for several reasons:

1. They are quick and easy, and can handle large numbers of series in an efficient manner.

2. They require only a small amount of data and are normally inexpensive to perform.

3. They provide accurate short- to mid-term forecasts.

Self-projecting methods do not, however, account for any external factors that may influence the time series being forecasted (9:9-10).

Cause-and-effect methods of time series forecasting account for external influences by the use of mathematical relationships between the series being forecasted and any number of other series representing the influencing factors. These methods are useful because:

1. More information is available concerning the forecast.

2. Interrelationships between many factors are taken into account.

3. Accurate forecasts can be provided for the mid- to long-term.

Cause-and-effect methods of time series forecasting require larger amounts of data and usually require more time and money to perform compared to other methods (9:10-11).

The time series model used in this thesis and explained further below is the Box-Jenkins model. Box-Jenkins (BJ) models use past values of the data and/or error terms in the model development. A simplistic example of a BJ model is in Equation (5).

$$Y_t = F_t + E_t \tag{5}$$

where: Y_t = time series
F_t = any patterns
E_t = random error term. (2:12.16; 9:17)

The BJ method involves four phases in the model building process, including:

1. Pattern identification.
2. Model specification.
3. Model diagnosis.
4. Hypothesis testing and forecasting.

In building a forecasting model for a particular time series, the process above becomes an iterative one. The final model selection from those specified in this iterative process is based on comparisons of the diagnostic checks conducted in the third step. The following text more clearly defines each of these four steps.

First, the underlying patterns in the raw data must be identified (i.e. trend, seasonality, cycle). Visual inspection of the data plot allows possible identification of an array of patterns. A pattern, opposite of randomness, is defined as a reoccurrence of data. One type of pattern is known as trend. A trend occurs when the variance of the data remains the same, but the mean may change either up or down. If the mean of the data remains constant, then no trend exists and the data are referred to as stationary. Seasonality, a second pattern, is defined as periodicity within the data. Seasonality may occur every 12 periods within monthly data or every four periods within quarterly data. Another pattern is cyclical in nature and is identified by a consistently rising or falling pattern over time. Cyclical and seasonal patterns differ in that a cyclical pattern normally includes two or more seasonal ones. (2:12.16; 3; 9:46; 11:14-16).

Next, the appropriate model must be specified based on the identified patterns. In specifying the appropriate BJ model based on the patterns identified, there are an array of choices. The basic BJ model, assuming stationarity, has two basic parameters: autoregressive parameters (AR) and moving average parameters (MA) (9:48-49).

The AR parameters use past values, or patterns, of the variable to predict future values as shown in Equation (6).

$$Y_t = \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + E_t \qquad (6)$$

where: Y_t = the time series
Φ_p = the AR parameter
p = order of the model
Y_{t-p} = past values of the time series
E_t = the error term. (9:49-50)

The MA parameters use the random errors, or error terms, occurring in past time periods to predict the time series value at time t as shown in Equation (7). MA forecasting models do not depend on past values of the time series in computing forecasts.

$$Y_t = -\Theta_1 E_1 - \ldots - \Theta_q E_{t-q} + E_t \qquad (7)$$

where: Y_t = the time series
Θ_q = the MA parameter
q = order of the model

E_{t-q} = the error term. (9:51)

When specifying a model based on the patterns identified, AR and MA parameters may be included in the same model. These types of models are referred to as ARMA models and follow the format in Equation (8).

$$Y_t = \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} - (\Theta_1 E_{t-1} + \ldots + \Theta_q E_{t-q}) + E_t \qquad (8)$$

where: Y_t = the time series
Φ_p = the AR parameters
Y_{t-p} = past values of the time series
Θ_q = the MA parameters
E_{t-q} = past values of the error term. (9:52)

If the identified patterns reveal the time series to be nonstationary, differencing of the data eliminates this nonstationarity. Differencing a series involves subtracting the first value of the series from the second, the second from the third, and so on (11:36). ARMA models that include differencing are referred to as autoregressive, integrated, moving average (ARIMA) models (Equation (9)).

$$Z_t = \Phi_1 Z_{t-1} + \ldots + \Phi_p Z_{t-p} - (\Theta_1 E_{t-1} + \ldots + \Theta_q E_{t-q}) + E_t \quad (9)$$

where:
Z_t = the differenced (stationary) time series
Φ_p = the AR parameters
Z_{t-p} = past values of the differenced time series
Θ_q = the MA parameters
E_{t-q} = past values of the error term
E_t = the error term. (9:129,138; 17:529-538)

The third step is to diagnose the model using certain "tools" or computer outputs. These tools are explained in the methodology.

Finally, after the model passes the diagnostic checks, the forecast must be conducted (2:12.16-12.17; 3; 9:47; 11:251-254).

Methods of Measuring Forecast Accuracy. Several methods exist to measure the accuracy of forecasting methods, and the resultant measurement values can be used to compare different forecasting methods. The accuracy measurement method used is important because it may determine which forecasting method is actually used to forecast into the future (2:12.17). Several accuracy measurement methods exist including:

1. Average error (AE).
2. Mean absolute deviation (MAD).
3. Mean square error (MSE).
4. Standard deviation (SD).
5. Mean absolute percent error (MAPE). (19:113-115)

Many of these methods are based on the error of the forecast. This error is many times referred to as the error term, forecast error or bias, random error component, or randomness. No matter what it is referred to as, the random error, or error term, is almost always denoted by E or e in any equation or formula. The error term is defined as:

> The part of a series that has no explanation outside of chance alone. That is, any data collected to represent some process or activity will always be in error owing to measurement errors or outside random influences. Each data value in a time series, therefore, is expected to be in error from the "true" value for that period. The manner in which these errors occur is generally assumed to be random. (If they weren't, they would demonstrate some relationship and therefore be part of the pattern component.) (9:271)

In regression, as well as any other forecasting model employing the error term, basic assumptions about the term are usually made. These assumptions are:

1. The has a normal distribution with a mean of zero and a standard deviation of σ.

2. The error terms for each time period are independent of one another (16:339).

The average error (AE) is the sum of the forecast errors divided by the number of forecast periods. The AE, expressed mathematically in Equation (10), usually understates the magnitude of the forecast error; however, the sign of the AE helps to reveal the direction of forecast error (19:113).

$$AE = (E_1 + E_2 + . . . + E_n) / n \tag{10}$$

where: E_n = the error in the n^{th} time period
n = number of periods in the series.

The mean absolute deviation (MAD) provides an accurate measurement of the magnitude of the forecast error. The MAD, expressed in Equation (11), is the sum of the absolute values of the forecast errors divided by the number of forecast periods.

$$MAD = (|E_1| + |E_2| + . . . + |E_n|) / n \tag{11}$$

where: $|E_n|$ = absolute value of the error at time period n
n = number of periods in the series.

While the MAD is an accurate measure of the forecast error, the use of absolute values in the MAD removes any evidence of forecast bias (19:113).

As expressed in Equation (12), the mean square error (MSE) is the sum of the squared forecast error values divided by the number of forecast periods (19:113).

$$MSE = (E_1{}^2 + E_2{}^2 + . . . + E_n{}^2) / n \tag{12}$$

where: $E_n{}^2$ = the squared value of the error at period n
n = number of periods in the series.

The MSE gives more importance to large errors in its computation than small errors. The MSE also removes any evidence of forecast bias (11:19).

The standard deviation (SD), shown in Equation (13), is the square root of the sum of the squared forecast error values divided by the number of forecast periods minus one (19:115).

$$SD = [(E_1{}^2 + E_2{}^2 + \ldots + E_n{}^2) / (n - 1)]^{1/2} \qquad (13)$$

where: $E_n{}^2$ = the squared value of the error at period n
n = number of periods in the series.

The SD does not give an indication as to the direction of the forecast error.

Finally, the mean absolute percent error (MAPE) finds the absolute percentage error for each individual forecast and computes the average of these forecasts as a whole. The MAPE, shown in Equation (14), has the advantage of allowing comparisons between different time series which is not permitted or possible when using the MSE (11:19). This advantage is due to the fact that the MAPE expresses the forecast error as a percentage of the mean of the data being forecasted.

$$MAPE = \{[(|E_1|/Y_1) + \ldots + (|E_n|/Y_n)] / n\} 100\% \qquad (14)$$

where: E_n = the error at period n
n = number of periods in the series
Y_n = the actual tonnage at period n.

In using any of these accuracy measurement methods to compare a group of forecast models, the model exhibiting the smallest accuracy measurement value can be said to be the most accurate in the group.

Current AFLC/DSXR Forecasting Methodology

As stated previously in Chapter I, AFLC/DSXR uses a linear regression methodology for SDT budget forecasting. Developed in the mid-1970s, it proceeds as follows:

1. The 40 most recent quarters of historical tonnage and flying hour data are obtained, broken down by overseas geographical region. The tonnage is also subdivided by means of transport.

2. A series of linear regressions, beginning with the initial 40 quarters of data, are conducted using Equation (15).

$$Y = \beta_0 + \beta_1 X \tag{15}$$

where: Y = the dependent, or forecasted, variable SDT tonnage
X = the independent variable flying hours
β_0 = the Y-axis intercept
β_1 = the independent variable parameter value, or the slope of the line.

During each subsequent regression, the number of quarters of data is decreased by eliminating the oldest quarter of data. The final regression iteration uses the eight most recent quarters.

3. For each regression, the coefficient of correlation (R), standard deviation, and tonnage forecasts are computed.

4. The regression with the highest R value is chosen as the equation to use, and the resulting tonnage forecasts are utilized to compute the SDT budget estimates.

AFLC/DSXR also applies a smoothing technique to remove the random variation within the data. After this application, the 4-step procedure above is repeated. The final choice between this latter technique and the technique initially discussed above is arbitrary. The guidelines for directing this choice are consistency of technique use over a period of time and thorough comparisons of the forecasts to the most recent historical tonnage (1:3-4; 12).

Previous Reports and Studies

The need for an accurate predictor of tonnage to use in computing budget requirements is not new. In fact, over the past several years, many reports have been written concerning this subject (1; 7; 8; 10). The reports and studies reviewed in this chapter were conducted on the method currently utilized by AFLC/DSXR to predict SDT tonnage.

Foster Study (1977). During an SDT review conducted by the Office of the Secretary of Defense (OSD) in 1976, the reviewer raised concern about the validity of AFLC's forecasting method for predicting SDT tonnage and its reliance on the flying hour program (7:1). This study, conducted and written by Newton W. Foster for the Directorate of Management Sciences, Deputy Chief of Staff Plans and Programs, Headquarters Air Force Logistics Command (HQ AFLC/XRS), was in direct response to the OSD review.

The objectives of the study were:

1. To support the use of flying hours as a predictor of SDT.

2. To develop a better method of predicting SDT if the flying hour related computation could not be supported (7:1).

Regression analysis was used in conducting this study and the data used as variables in this technique were relatable to transportation. Sixteen quarters of data, from FY 73/1 through FY 76/4, were collected and categorized under 21 different headings (i.e. manpower, requisitions. overseas flying hours, worldwide flying hours). These data were collected by six major geographical regions: PACAF, USAFE, AAC, USAFSO, Northeastern, and Worldwide. The means of transport within each region in which data were collected were: MAC, MSC, and GBL (worldwide only) (7:3-4).

Two types of regression were used: simple linear regression and multiple regression. Functionally, these regressions are expressed in Equation (16).

$$Y = f(X_i) \tag{16}$$

where: Y = SDT tonnage, the dependent variable
X_i = the independent variable; for simple linear regression - any one of the 21 categories, and for multiple regression - any combination of the 21 categories.

These analyses were conducted on each mean of transport for each geographical region using the 21 categories of data as independent variables. Simple linear regression involved two variables: SDT, the dependent variable; and each of the 21 data categories taken one at a time as the independent variable. Multiple regression involved the use of more than one independent variable and the dependent variable (7:4-5).

The conclusions of this study were:

1. The forecast method, although not a totally valid predictor of SDT tonnage, was the most logical predictor based on the data provided and examined.

2. A better forecasting method for predicting SDT tonnage for a particular geographical region by a specific transportation mode was not evident based on the data provided and examined (7:6).

Grayson Research Study (1977). Major John Grayson, an Air Command and Staff College (ACSC) student, conducted research for partial fulfillment of the requirements for ACSC graduation. Conducting this research as a result of its direct utility to the Air Force, Grayson stated:

> Increasingly austere funding has challenged the Air Force to maintain, and even improve, operational readiness of the fleet with fewer available spares. One step toward meeting this challenge has been increased reliance on the transportation network to provide more timely distribution, or redistribution of available spares from supply to user locations. (8:1)

He further noted that funding for this transportation network, including SDT, had long been a problem within the Department of Defense. The purpose of this study was to investigate AFLC's method for determining SDT requirements and ultimately offer recommendations to improve the process (8:4).

In reviewing the AFLC forecasting method and its reliance on the Air Force flying hour program (FHP), Grayson concluded that "...there is an overreliance on the FHP in determining SDT requirements" (8:24-25). Grayson theorized that using flying hours as the sole independent variable to predict SDT (shown in Equation (17)) assumed a statistical insignificance of many other variables impacting SDT.

$$Y = f(X) \tag{17}$$

where: Y = SDT tonnage, the dependent variable
X = regional flying hours, the independent variable.

Two examples of other potentially significant variables were manpower and differing amounts of logistical support per flying hour for different types of aircraft (8:17,19).

Grayson, as a result of this research, recommended two actions be taken. First, efforts should continue by the Air Staff and AFLC to identify programs whose cargo can be separated from the general cargo classification. Since the SDT tonnage included in the general cargo category is predicted from the FHP, the separation of other cargo classifications would reduce the overall percentage of SDT tonnage dependent on the FHP. Secondly, it was recommended that AFLC identify other potential factors influencing SDT and develop a multivariate model (8:25-26).

Lamb-Sarnacki Thesis (1978). Captains Christopher J. Lamb and Joseph B. Sarnacki, Air Force Institute of Technology (AFIT) graduate students, stated the problem was the lack of a valid forecasting method for predicting SDT tonnage and, thus, an inability to compile accurate SDT budget estimates. The objectives of this thesis were to:

1. Determine the significance of flying hours and manpower as reliable predictors of SDT.

2. Develop a computer model to predict future SDT tonnage if either or both of these variables were proved reliable (10:1,10).

The forecasting technique used in this thesis was discontinuous linear regression (DLR). This technique is used whenever a linear regression function changes slope and at the same time shifts vertically up or down, and the researchers believed this to be the case. An additional variable was needed to account for this vertical shift in the data (10:15; 15:316). Equation (18), quoted directly from the thesis, functionally defines the general form of the DLR model used.

$$\begin{aligned} Z = {} & B_0 + B_1X + \{b_2(X-X_1)\ X_{p1} + B_3X_{D1}\}^* \\ & + \{B_4(X-X_2)X_{p2} + B_5X_{D2}\}^* \\ & + \{B_6(X-X_3)\ X_{p3} + B_7X_{D3}\}^* \\ & + B_8Y + \{B_9(Y-Y_1)Y_{p1} + B_{10}Y_{D1}\}^* \\ & + \{B_{11}(Y-Y_2)Y_{p2} + B_{12}Y_{D2}\}^* \\ & + \{B_{13}(Y-Y_3)Y_{p3} + B_{14}Y_{D3}\}^* + e \end{aligned} \tag{18}$$

* Discontinuity adjustments

where: Z = Tonnage transported by MAC,

X = Flying hours (either programmed or actual),

Y = Manpower (either programmed or actual),

$X_1, X_2, X_3, Y_1, Y_2, Y_3$ = Points where data becomes discontinuous,

$X_{p1}, X_{p2}, X_{p3}, Y_{p1}, Y_{p2}, Y_{p3}$,

$X_{D1}, X_{D2}, X_{D3}, Y_{D1}, Y_{D2}, Y_{D3}$ = Indicator (dummy variables) defined as:

$X_{p1} = X_{D1} = 1$, if $X > X_1$; otherwise 0

$X_{p2} = X_{D2} = 1$, if $X > X_2$; otherwise 0

$X_{p3} = X_{D3} = 1$, if $X > X_3$; otherwise 0

$Y_{p1} = Y_{D1} = 1$, if $Y > Y_1$; otherwise 0

$Y_{p2} = Y_{D2} = 1$, if $Y > Y_2$; otherwise 0

$Y_{p3} = Y_{D3} = 1$, if $Y > Y_3$; otherwise 0

$B_0, \ldots, B_{14}$= Coefficients of regression, and

e = The explained component in each value that is not explained by the independent variables. (10:18-19)

Only MAC data were evaluated and separate models were derived for each of five geographical regions (European, Pacific, Alaskan, Southern, and Northeastern) as well as the total database. The thesis concluded that the models developed were more accurate than the current method employed by AFLC based on the mean absolute deviation (MAD) (10:38).

Several advantages were noted for using the method developed in this thesis including:

1. The lack of necessity for an arbitrary base period for each area since SDT estimates would now relate to direct changes in flying hours and manpower

2. Faster results could be obtained from the use of a computer-assisted software package such as the Statistical Package for the Social Sciences (SPSS) used in this 1978 AFIT thesis.

3. A more accurate and valid estimate of quarterly SDT tonnage would be provided.

Abell Study (1982). In 1982, Joseph A. Abell conducted an evaluation of AFLC's forecasting method. Abell stated:

> The rationale for the use of flying hours as an indicator of tonnage movements is a result of past experience. That is, it has been shown that in most of the five geographical areas served by MAC and MSC, the variation in the trends in tonnage movements can be related to the variation in the number of hours flown in the specific geographical area. If it is assumed that past relationships will remain fairly constant, then it can also be assumed that one variable, programmed flying hours, can be used to predict another, tons. (1:1)

Initially, Abell believed duplication of prior forecasts was necessary to properly evaluate AFLC's forecasting method; however, as a result of the inability to duplicate the forecasts, a study evolved to determine the reason for this disagreement. An evaluation of the data smoothing technique employed by AFLC was also conducted to determine its effect on the data and forecast accuracy (1:5).

Abell used the CREATE system and the Statistical Package for the Social Sciences (SPSS) to:

1. Develop scattergrams of the data used in the regressions.

2. Estimate the regression equations and accompanying statistics.

3. Compute necessary statistics on each of the individual variables (1:5).

Simple linear regressions were conducted on all five areas (Europe, Pacific, Alaska, Southern, and Northeastern). An evaluation of the October 1981 forecasts was also conducted (1:6).

Throughout his research, Abell was unable to duplicate the results of the regressions being evaluated. However, he stated:

> The nonduplication of prior results, again, does not mean that the use of linear regression is invalid. To me it meant that there was a "kink" in computer program currently used and that it could be corrected. (1:6)

Abell used three checks for computational accuracy applicable to linear regression. First, the regression line must pass through a point (X,Y), where X is equal to the sum of the flying hours for a particular region divided by the total number of observations, or:

$$X = (X_1 + X_2 + \ldots + X_i) \;/\; n \tag{19}$$

where: X_n = flying hours at period i (where i = 1,2,...n)
n = the total number of observations.

Secondly, by substituting X into the developed regression equation, Y becomes: $Y = a + bX$. Any deviation from the actual value of Y would then be considered forecast error. The final check involved substituting the actual X value into the developed regression equation and subtracting this result from the actual Y value. The sum of these differences should be zero. Abell determined AFLC forecasting method was devoid of computational accuracy. This discovery led to search for the cause (1:6-8).

Abell assumed as each new regression was conducted, it was done so independent of all other regressions. He also assumed the data used for each regression would produce the same results -- or simply stated, the results were replicatable. Abell, however, found these assumptions false (1:8).

Abell concluded there was a "kink" in AFLC's program that added together the total number of observations from all previous regressions with the number of observations in the next to last regression. For example, if the first regression was run with 40 observations, the second regression used 40 + 39 = 79 observations; 40 + 39 + 38 = 117 observations were used in the third, and so on. The number of observations should have decreased by one during each successive regression. For example, if 40 observations were used in the initial regression, then 39 would be used in the second, 38 in the third, until the last regression was conducted with the eight most recent observations. Abell believed this "kink" generated forecasts incapable of being duplicated (1:9).

Abell offered the following conclusion:

> The use of regression analysis as a method to forecast future tonnage movements over MSC and MAC should be continued and is appropriate for the following reasons:
>
> 1) it is dependable and defendable
>
> 2) it is able to incorporate the effects of past trends into the estimate
>
> 3) it is able to incorporate indicators of increases/decreases of future operations into the estimate
>
> 4) provides a measure of the probable error in the estimate
>
> 5) provides a measure of the strength of the relationship between tonnage movements and flying hours, the correlation coefficient. (1:22-23)

Interpretation of Previous Reports and Studies. It can be inferred from these reports and evaluations that there is disagreement as to the validity of AFLC/DSXR's forecasting method. The reports reviewed in this chapter have shown the current method utilized is suspect and therefore questionable as a forecasting tool. However, only the Lamb-Sarnacki thesis offered a solid alternative to the current method, but it was never implemented. One observation, in reviewing these sources, is that no attempt has been made to use more sophisticated forecasting techniques such as ad hoc or time series methods. These techniques include Holt's Two Parameter, Winter's Three Parameter, and Box-Jenkins methods.

III. Methodology

The primary objective of this research was to validate the current forecasting method used by AFLC/DSXR to compute SDT tonnage estimates. If the method's validity as a forecasting tool could not be supported, an attempt would be made to develop a valid model using the same input data. This chapter explains the methodology followed in conducting this research.

Data Acquisition

To initiate this research, the necessary flying hour and SDT tonnage data were obtained from AFLC/DSXR. This office gathers this data in order to accomplish its current forecasting. Historical quarterly data for flying hours and SDT tonnage were obtained for FY 78/1 through FY 87/4. As explained in Chapter I of this thesis, shipments by MAC and MSC to PACAF and USAFE account for 87 percent of AFLC's SDT funding for overseas areas. Actual quarterly SDT tonnage data were also collected for FY 88/1 through FY 89/2 in order to compare the forecasts for these same quarters. These data are included in Appendix A.

Current Model Validation

In conducting this research, no exact method could be found to evaluate the type of model AFLC/DSXR utilizes; however, after reading literature on this subject, it was determined that if the flying hour parameter (β_1 in equation (20)) in the model could be shown to change statistically after any iteration was conducted, the model was structurally unstable. In using this iterative linear regression approach, AFLC/DSXR assumes that β_1 does not change and, therefore, that the data are stationary. However, if β_1 does change, this iterative approach becomes invalid.

$$Y = \beta_0 + \beta_1 X \tag{20}$$

where: Y = the dependent, or forecasted, variable SDT tonnage
X = the independent variable flying hours
β_0 = the Y-axis intercept
β_1 = the flying hour parameter, or the slope of the line.

If this instability was present, it implied the model was invalid. In addition, this instability would indicate nonstationarity within the data, and therefore the iterative linear regression approach would not be useful in predicting future values of the time series.

In an attempt to determine the stability of the flying hour parameter as successive iterations of the forecast model were conducted, the following steps were conducted.

1. The flying hour parameter, β_1, for each iteration was computed. These values were computed using QUATTRO, a spreadsheet software package developed by Borland International.

2. The standard error ($s_{\beta 1}$) for each flying hour parameter was computed with the use of QUATTRO.

3. Using these standard errors, 95 percent confidence intervals for β_1 were established for each iteration using equation (21) (15:58-60; 16:492-493).

$$\beta_1 \pm t_{\alpha/2} s_{\beta 1} \tag{21}$$

where: $t_{\alpha/2}$ = the value of the two-tailed test-statistic for α = .05 and n - 2 degrees of freedom.

4. If any two of these confidence intervals did not overlap, then the model was showed structurally unstable, and was, therefore, invalid as a forecasting tool.

The null hypothesis (H_0) for validating the current model was that the flying hour parameters (β_1 in equation (20)) for each regression iteration were equal. H_0 thus implied the current forecasting model used by AFLC/DSXR was stable and valid.

The alternate hypothesis (H_A) was that at least one of the flying hour parameters of any regression iteration was not equal to the others. H_A therefore implied the model was structurally unstable and therefore invalid. If this was the case, it was also inferred that the data was nonstationary.

The decision rule, or test statistic, shown in equation (21), was used to draw inferences about the parameters. H_0 was rejected if the decision rule proved that any one of the flying hour parameters was not equal to the others; otherwise, the H_0 was not rejected.

The hypothesis testing was conducted based on the following format:

H_0: $\beta_{1,8} = \beta_{1,9} = \ldots = \beta_{1,40}$

H_A: $\beta_{1,i} \neq \beta_{1,8} = \ldots = \beta_{1,n}$

where: i = any one iteration conducted with 8 to 40 periods of data
n = total number of iterations conducted excluding i

Test Statistic: $\beta_1 \pm t_{\alpha/2} s_{\beta 1}$

where: $t_{\alpha/2}$ = the value of the test-statistic for α = .05 and n - 2 degrees of freedom (df).

Rejection Region: Reject H_0 if any two of the regression iteration confidence intervals did not overlap.

QUATTRO was used for conducting this hypothesis testing.

Model Application

SDT tonnage forecasts were obtained using AFLC/DSXR's forecasting method, where a series of linear regressions, beginning with the last 40 quarters (FY 78/1 through 87/4) of historical data, were conducted using equation (22).

$$Y = \beta_0 + \beta_1 X \tag{22}$$

where: Y = the historical SDT tonnage
X = the historical flying hours
β_0 = the y-axis intercept
β_1 = the flying hour parameter, or the slope.

During each subsequent regression, the number of quarters of historical data was decreased by eliminating the oldest quarter of data. The last regression was conducted utilizing the eight most recent quarters of historical data. The model producing the highest coefficient of correlation (R) was selected as the forecasting model. R is described functionally in equation (23).

$$R = \pm [1 - (SSE / SSTO)]^{1/2} \qquad (23)$$

where: SSE = the variation in the dependent variable (Y), or SDT tonnage, when the independent variable (X), or flying hours, is used in the regression model

SSTO = the variation in Y when X is not taken into account. (15:89-90)

Model Building

Predicated on instability, Box-Jenkins (BJ) time series modeling was chosen as the method to use in developing a new model to forecast SDT tonnage. This choice was made because BJ identifies patterns in the history of a time series and uses these patterns to develop the appropriate model.

In conducting the BJ model building and forecasting process a computer software package was used. TIMES, mainly written at The Ohio State University, was used for this time series analysis and forecasting. The necessary output to evaluate and select the final models chosen was also obtained using TIMES.

In building a Box-Jenkins time series model, four distinct steps were followed.

1. A plot of the raw data as well as other statistics (i.e. the autocorrelation function, ACF, and the partial autocorrelation function, PACF) were compiled and reviewed to identify any underlying patterns within the data (i.e. trend, seasonality, etc.). The ACF uses statistical measures to determine the strength of correlation of time series values at a certain number of periods apart. It determines the relation of a time series to itself over time. The PACF also uses statistical measures to determine the strength of other relations within the time series (9:54-56). These ACFs and PACFs were compiled using TIMES. In evaluating these functions, the values at lags one through three were considered significant if they were greater than one-half of the corresponding standard error. The values at lags four through six were considered significant if they were larger than the standard error. If the values at lags seven through nine were greater than two times the corresponding standard error, they were considered significant. Finally, all the remaining lagged values were significant if they were at least three times as large as the corresponding standard error.

2. Based on these patterns, an appropriate ARMA or ARIMA model was specified with estimated AR and MA parameters from the 40 quarters of time series data.

3. Diagnostic tests were conducted on the model to ensure it was an accurate and appropriate model. There were

eight tests conducted including:

a. The residuals were plotted and reviewed. Ideally, the mean of the residuals should be zero or near zero. There should also be no change in the variance of the residuals. If these conditions are not met, there is a problem in the model in that all the patterns within the time series have not been accounted for by the specified model.

b. The residual autocorrelation function (ACF) was inspected. If there are any significant values, or "spikes", at any of the lags, the model does not explain all the variation in the data.

c. The Portmanteau Lack of Fit Test value, or the Q-statistic, was evaluated. Ideally, the value should be small compared to other Q-statistics with the same number of degrees of freedom. If it becomes too large, the model does not fit the data (9:93-94; 17:549-550).

d. The cumulative periodogram of the estimated residuals, or errors, was evaluated. The periodogram should be linear or very close to linear, otherwise, the residual variation in the model cannot be attributed to purely random processes.

e. A histogram of the residuals was reviewed. The residuals should be normally distributed about zero with a constant variance. If the histogram was mound-shaped and centered about zero, this assumption was considered true.

f. The sum of the squared errors (SSE) and the mean squared errors (MSE) of each time series were evaluated. Ideally, these values should be small. Large values indicate the model was not a good predictor of the time series.

g. The Fourier Transform of the autocorrelations, or Power Spectrum, was evaluated. This graph should be smooth and horizontal, and anything to the contrary implies a problem in the model.

h. The Schwarz statistic, or the Bayesian Information Criterion (BIC), was reviewed. Equation (24) was used to compute the BIC which assesses goodness of fit as well as penalizing for complexity within the model. This complexity is concerned with the number of parameters in the model. The BIC, ideally small in size, normally leads to models of lower orders than other similar statistical tests.

$$BIC = SSE * n^{(p+q)/n} \tag{24}$$

where: SSE = the sum of the squared errors
n = the number of periods in the data
p = the number of autoregressive parameters
q = the number of moving average parameters.

As seen from Equation (24), if two models have nearly the same SSE, but one of the models has more parameters than the other, the model with fewer parameters would be chosen.

4. Finally, after a model was built that passed these tests with stability, the forecast was conducted (3; 9:90-97; 17:548-552). The forecasts were conducted using TIMES

and the models developed during this building process.

An important point here is that this 4-step process is iterative in nature and therefore more than one model is usually specified before a final choice is made. This allows for a comparison of the diagnostics between the models. For this research, only the final models for each of the four data sets will be discussed.

Forecast Accuracy Measurement

As explained in Chapter II, there are several accuracy measurement methods that can be used to compare the accuracy of forecasts between different models. The choice of accuracy measurement method is important because it may determine which forecasting method is ultimately used.

The mean absolute percent error (MAPE), shown in equation (25), was used to compare the forecasts of AFLC/DSXR's method and the models built during this research.

$$MAPE = \{[(|E_1|/Y_1) + \ldots + (|E_n|/Y_n)] / n\} \; 100\% \qquad (25)$$

where: E_n = the error at period n
n = number of periods in the series
Y_n = the actual tonnage at period n.

The forecast errors for AFLC/DSXR's models were computed by subtracting the actual SDT tonnage from the forecasts. Likewise, the errors for the BJ models developed in this research were computed by subtracting the actual SDT tonnage from the predictions.

In comparing AFLC/DSXR's model and the models developed in this thesis, the forecast model producing the smaller MAPE was deemed to be more accurate.

Summary

This chapter laid out the steps used to conduct this research. The research began with data acquisition followed by a statistical test to validate, or invalidate, the current model as a forecasting tool. Next, the forecasts of the current model were verified by quickly calculating these values using the AFLC/DSXR method. Following these calculations, BJ models were built to forecast the four data sets being researched. Finally, the AFLC/DSXR models were compared to the BJ models for forecast accuracy. This methodology leads into the results and analysis discussed in Chapter IV.

IV. Results and Analysis

This chapter includes results obtained during research conducted for this thesis. The results were used to analyze the two objectives which served as guidance for this research. In addition, the results obtained were used to support or refute the research hypothesis. The research objectives will be restated, and results and analysis presented in the remainder of this chapter.

Research Objectives

Research Objective 1. Validate the current forecasting method used for computing tonnage estimates to derive SDT budget requests.

This research objective was accomplished by acquiring the necessary flying hour and SDT tonnage data from AFLC/DSXR for the 40 quarters from FY 78/1 through FY 87/4. As explained earlier, these data were for SDT tonnage shipments by MAC and MSC to USAFE and PACAF; therefore, four distinct data sets were compiled. In addition, the actual AFLC/DSXR SDT tonnage forecasts for the six quarters from FY 88/1 through FY 89/2 for these same sets were obtained to allow for accuracy measurement comparisons between the method currently used and the models developed in this research. Finally, data concerning the number of quarters used by AFLC/DSXR in each regression forecast for each data set were gathered to determine if the number of quarters were in the unstable range of the flying hour confidence intervals.

Another, and final, step in accomplishing this research objective was to determine if the flying hour parameter, β_1, in AFLC/DSXR's current model changed statistically after each regression iteration was conducted. If this change did occur, the model was considered statistically invalid. As stated earlier, a 3-step process was conducted on each data set to determine if any change of the flying hour parameter occurred.

1. The β_1 for each iteration was computed using QUATTRO.

2. The standard error ($s_{\beta 1}$) for each β_1 was computed using QUATTRO.

3. Using these standard errors, 95 percent confidence intervals for β_1 for each iteration were established.

Data Analysis. The data for all four sets were compiled and graphed by two methods. First, SDT tonnage, the dependent variable, was graphed against the independent variable, regional flying hours. Secondly, SDT tonnage was graphed over time.

As seen in Figure 2, MAC SDT tonnage shipped to USAFE, when graphed versus flying hours, is widely dispersed and appears curvilinear.

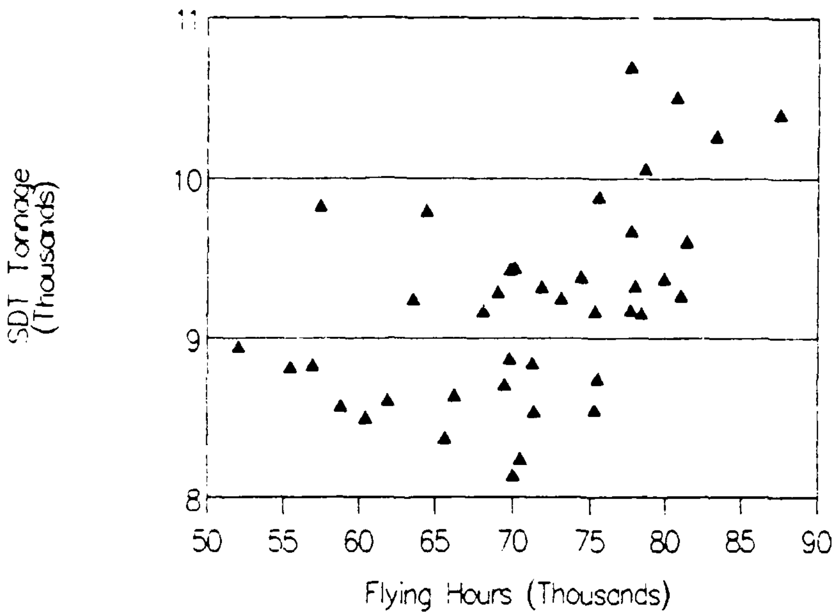


Figure 2. Regional Flying Hours versus MAC SDT Tonnage for USAFE

Figure 3 depicts MAC SDT tonnage shipped to USAFE as a time series. This relationship does not appear to be linear and constant, but rather curvilinear.

The relationship of MSC SDT tonnage shipped to USAFE to flying hours is depicted in Figure 4. This graph suggests a curvilinear heteroscedastic relationship of tonnage to flying hours.

Figure 5 exhibits MSC SDT tonnage shipped to USAFE as a time series. As evidenced by the graph, the series is curvilinear and nonconstant. There is no indication of a constant or linear relationship.

Figure 6 graphically relates MAC SDT tonnage shipped to PACAF to regional flying hours. As the figure suggests, no semblance of linearity exists between the two variables.

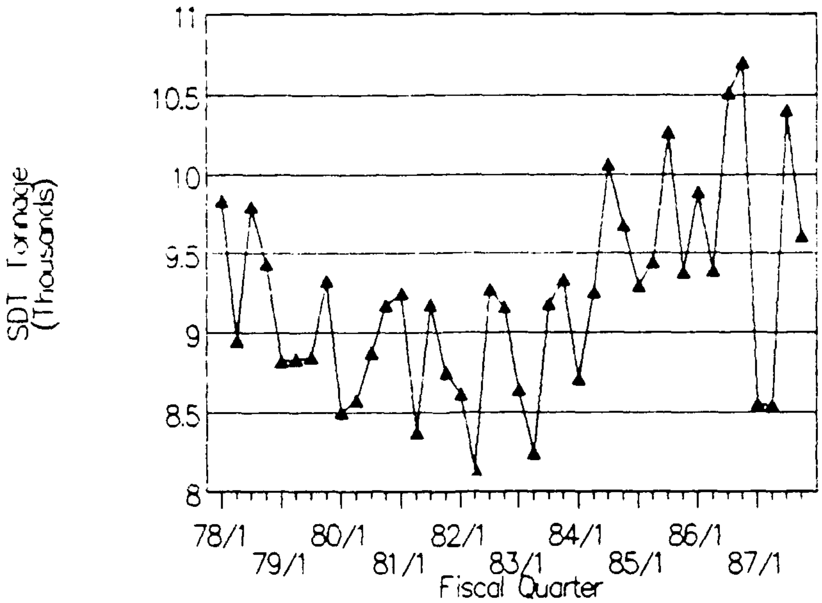


Figure 3. Quarterly SDT Tonnage Shipped to USAFE by MAC

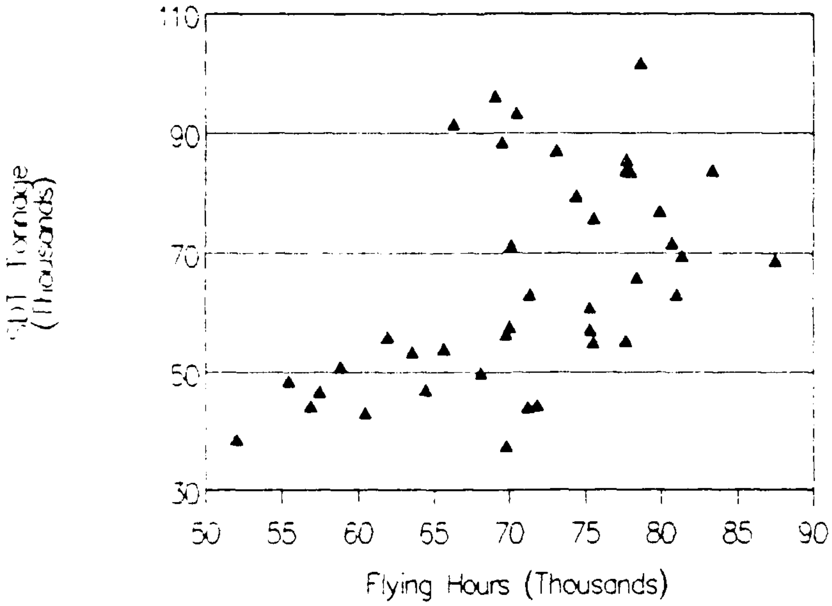


Figure 4. Regional Flying Hours versus MSC SDT Tonnage for USAFE

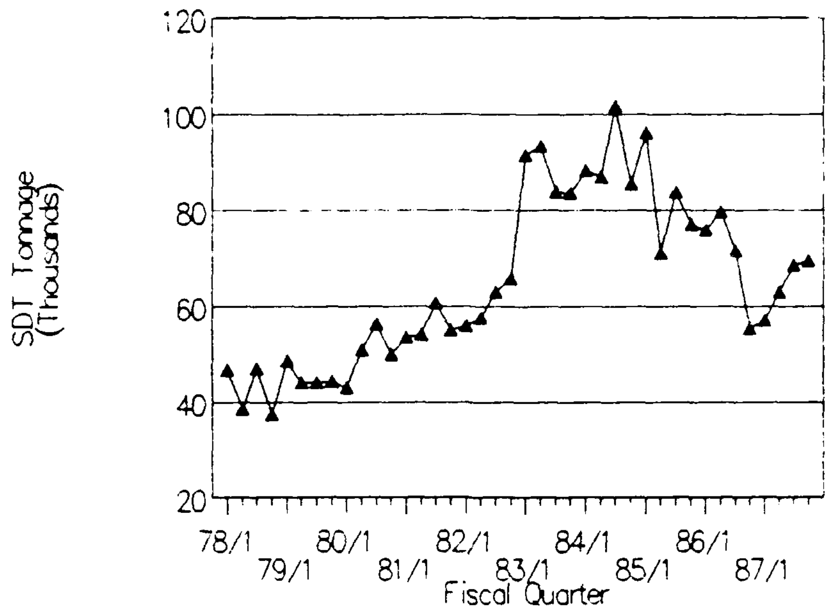


Figure 5. Quarterly SDT Tonnage Shipped to USAFE by MSC

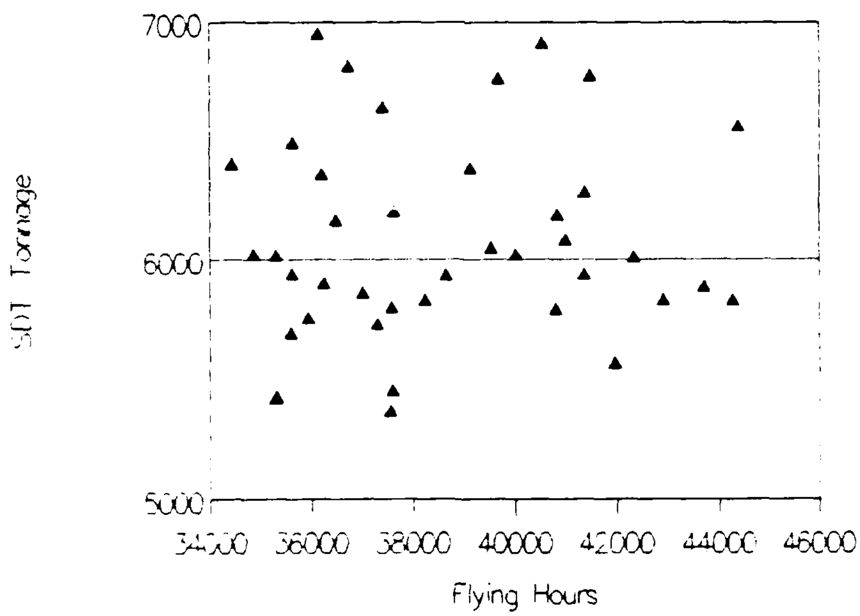


Figure 6. Regional Flying Hours versus MAC SDT Tonnage for PACAF

MAC SDT tonnage shipped to PACAF is expressed as a time series in Figure 7. The series appears linear with a slight upward trend.

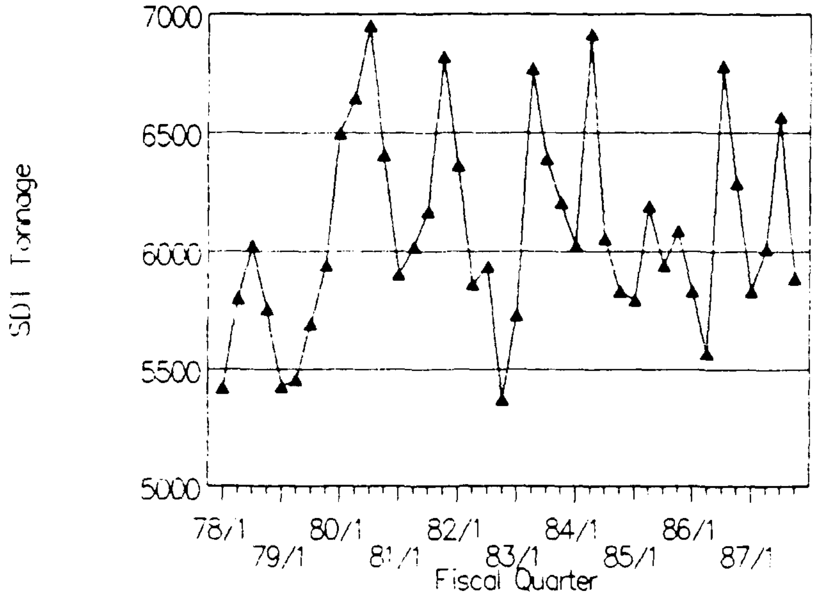


Figure 7. Quarterly SDT Tonnage Shipped to PACAF by MAC

Figure 8 shows MSC SDT tonnage shipped to PACAF plotted against flying hours. Although the graph appears linear at the lower range of flying hours, the variance within the data increases with the amount of flying hours.

MSC SDT tonnage shipped to PACAF is expressed as a time series in Figure 9. This series, although linear with a slight upward trend initially, becomes erratic with large variances in later periods.

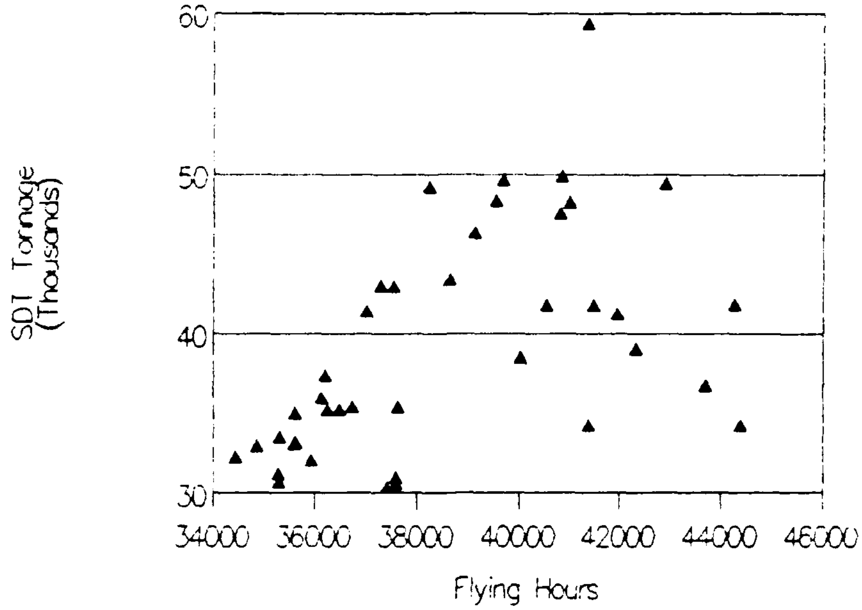


Figure 8. Regional Flying Hours versus MSC SDT Tonnage for PACAF

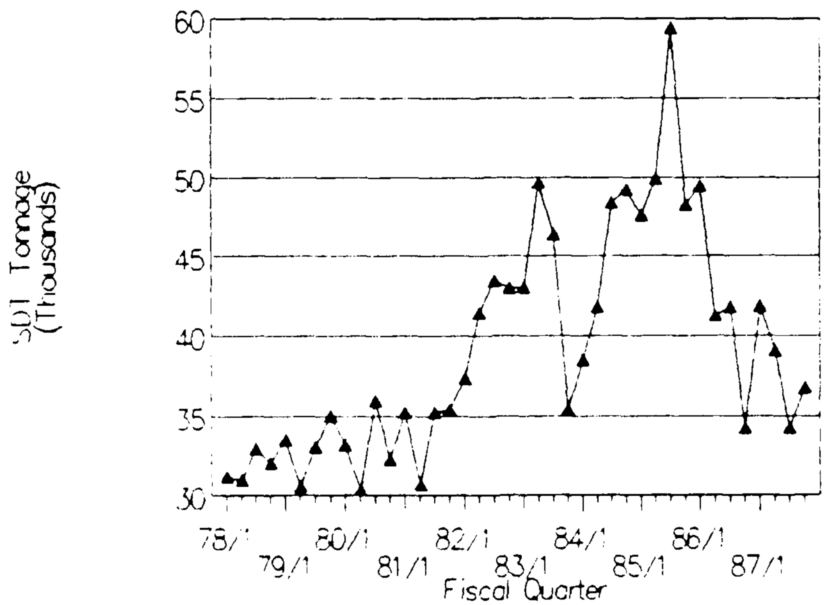


Figure 9. Quarterly SDT Tonnage Shipped to PACAF by MSC

The number of quarters used by AFLC/DSXR in each data set regression varied. The regressions for MSC SDT tonnage shipped to both USAFE and PACAF used 40 quarters. The regression for MAC SDT tonnage shipped to PACAF used 23 quarters, and 20 quarters were used for the MAC SDT tonnage shipped to USAFE regression.

Equations (26) through (29) present the linear regression models used by AFLC/DSXR to forecast the SDT tonnage for these data sets.

The linear regression used for MAC SDT tonnage shipped to USAFE is shown in equation (26).

$$Y = 2382.187 + 0.093162X \tag{26}$$

where: Y = the forecasted SDT tonnage
X = the flying hours associated with the quarter being forecasted
n = 20
R = 0.7175.

Equation (27) expresses the linear model used to forecast the MSC SDT shipped to USAFE.

$$Y = -15,202.7 + 1.127496X \tag{27}$$

where: n = 40
R = 0.5280.

The linear regression model used to forecast MAC SDT tonnage shipped to PACAF is shown in equation (28).

$$Y = 4874.293 + 0.029748X \tag{28}$$

where: n = 23
R = 0.1656.

Equation (29) was used as the linear model to predict MSC SDT tonnage shipped to PACAF.

$$Y = -11,070 + 1.302432X \tag{29}$$

where: $n = 40$
$R = 0.5235$.

The forecasted values for each of these linear regressions are shown in Table 4.

Table 4

AFLC/DSXR Forecasted Values for SDT Tonnage

	MAC SDT		MSC SDT	
FY	USAFE	PACAF	USAFE	PACAF
88/1	9,232	6,141	67,703	44,398
88/2	9,086	6,123	65,931	43,583
88/3	9,773	6,130	74,243	43,901
88/4	10,149	6,131	78,792	43,964
89/1	9,609	6,149	72,258	44,747
89/2	9,611	6,168	72,288	45,562

Current Model Validation. As stated earlier in this chapter, a 3-step process was conducted on each data set to statistically determine if changes occurred in the flying hour parameter after each regression iteration. The flying hour parameter and upper and lower confidence interval values for each regression iteration within each data set were graphed. These values are tabulated in Appendix B. The graphs indicate if any of the confidence intervals within a particular data set regression failed to overlap, thus invalidating the model.

As stated earlier in the thesis, the following hypothesis test was used to determine statistically whether or not the flying hour parameters for each regression iteration within a data set were equal.

H_0: $\beta_{1,8} = \beta_{1,9} = \cdots = \beta_{1,40}$

H_A: $\beta_{1,i} \neq \beta_{1,8} = \cdots = \beta_{1,n}$

where: i = any one iteration conducted with 8 to 40 periods of data
n = total number of iterations conducted excluding i

Test Statistic: $\beta_1 \pm t_{\alpha/2} s_{\beta 1}$

where: $t_{\alpha/2}$ = the value of the test-statistic for $\alpha = .05$ and $n - 2$ degrees of freedom (df).

Rejection Region: Reject H_0 if any two of the regression iteration confidence intervals did not overlap.

A failure of any two confidence intervals to overlap resulted in the failure to support the null hypothesis (H_0) of model stability. A failure of this type statistically invalidated AFLC/DSXR's current model as a forecasting tool.

Graphically, a failure of overlap occurred whenever the lower limit of one confidence interval within a data set was larger (horizontally higher on the graph) than the upper limit of another confidence interval within the same data.

Figure 10 shows the flying hour parameter confidence intervals for MAC SDT tonnage shipped to USAFE.

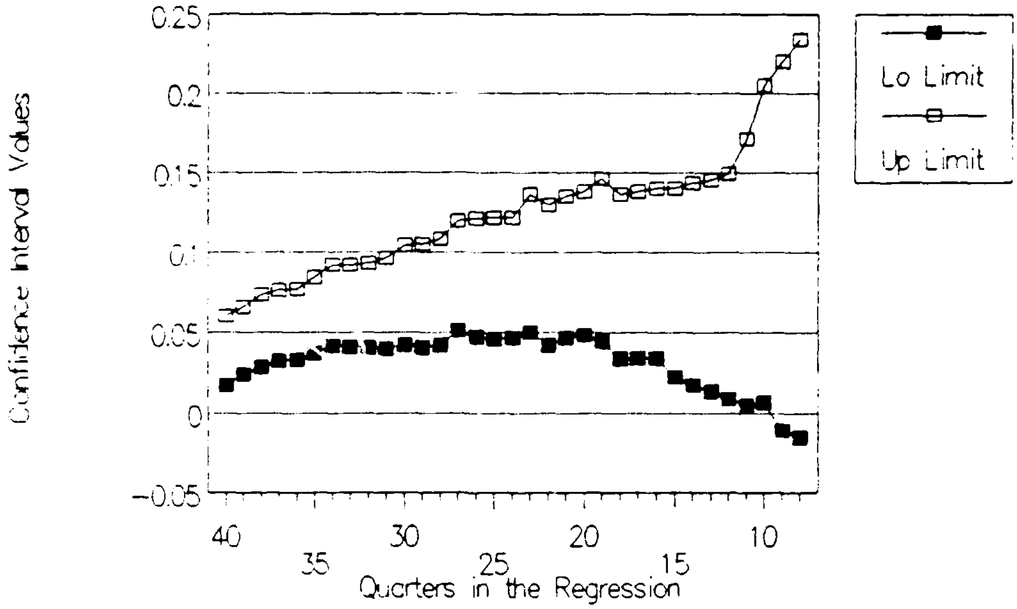


Figure 10. Confidence Intervals for the Flying Hour Parameter (MAC to USAFE)

Based on the graph in Figure 10, H_0 cannot be rejected for MAC SDT tonnage forecast for USAFE. The regression iteration using 27 quarters (lower limit of 0.0508) did, however, almost fail to overlap with the 40-quarter regression iteration (upper limit of 0.0598).

Figure 11 depicts the parameter confidence intervals for MSC SDT tonnage forecasted for USAFE. The graph in Figure 11 clearly exhibits several confidence intervals that do not overlap. Using this information, H_0 was rejected thus resulting in the conclusion that the flying hour parameter changed during the regression iterations.

Figure 12 shows all parameter confidence intervals for MAC SDT tonnage forecasted for PACAF overlapping.

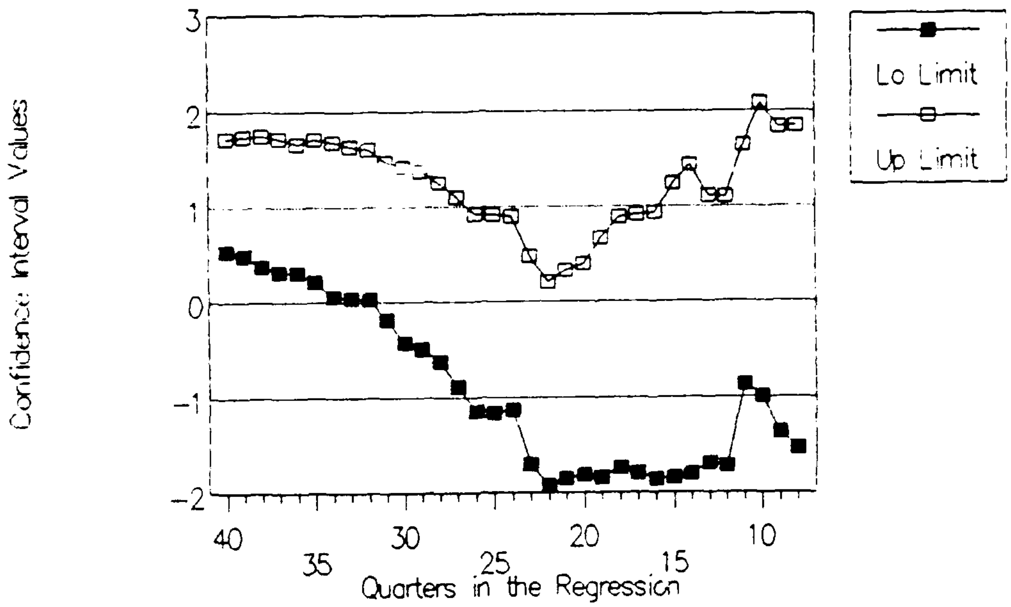


Figure 11. Confidence Intervals for the Flying Hour Parameter (MSC to USAFE)

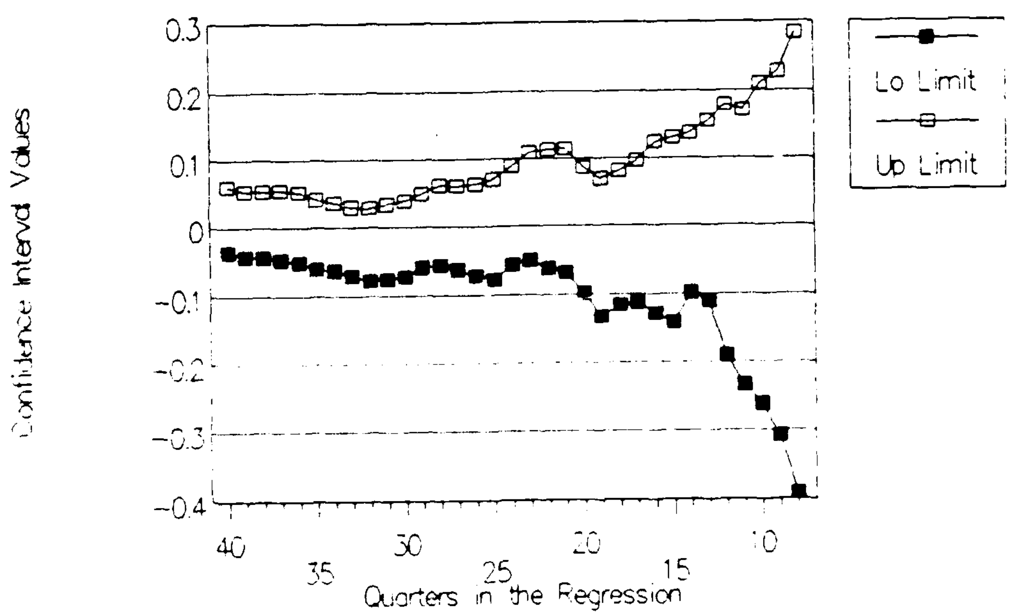


Figure 12. Confidence Intervals for the Flying Hour Parameter (MAC to PACAF)

Figure 13 exhibits parameter confidence intervals for MSC SDT tonnage forecast for PACAF. The graph shows, again, several confidence intervals not overlapping. These failures result in a rejection of H_0 leading to the conclusion that the parameter changed during the regression iterations.

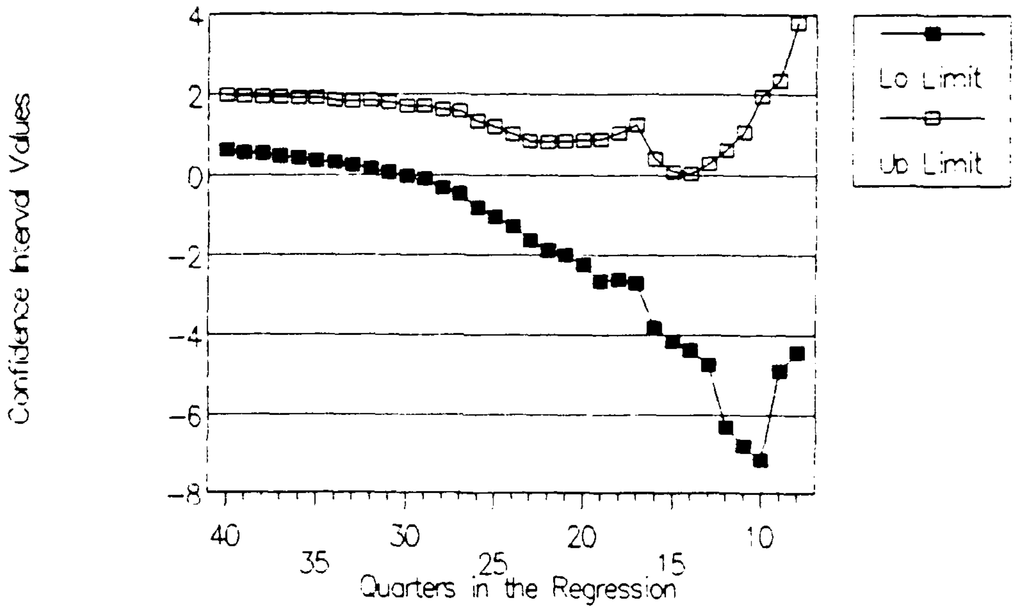


Figure 13. Confidence Intervals for the Flying Hour Parameter (MSC to PACAF)

In summary, the statistical test employed to determine the validity of the current model resulted in the two MSC SDT data sets, in fact, being statistically invalidated; however, the same test failed to statistically invalidate the two MAC SDT data sets. This result does, however, imply the current model, in general, is perhaps an ineffective forecasting tool.

Research Objective 2. If the current method's validity was not supported, develop a new forecasting model, using the same input data, that would produce more accurate and reliable tonnage estimates.

As noted above, the validity of the current method is suspect. Therefore, the second research objective was accomplished in two steps. First, Box-Jenkins (BJ) time series forecasting models were built for each of the four data sets. Secondly, the accuracy of these models was evaluated using the mean absolute percent error (MAPE). The MAPE was used because it enabled the size of the error in a particular period to be related to the actual tonnage in the same period; thus the MAPE offers the user the error as a size percentage of the actual tonnage.

As stated earlier in the methodology chapter, BJ time series forecasting was used to develop new models for each data set to forecast SDT tonnage. This choice was made because BJ enables patterns to be identified in the history of a time series and uses the patterns to build the appropriate model.

As stated earlier in Chapter II, four distinct steps were followed in building these BJ models.

1. Identification of any patterns in the time series.

2. Model specification based on these identified patterns.

3. Diagnostic tests to ensure the appropriate model is specified.

4. Hypothesis testing and forecasting.

Pattern Identification. Data plots, autocorrelation functions (ACFs), and partial autocorrelation functions (PACFs) were graphed and analyzed for each of the time series data sets to identify any underlying patterns within the series. The graphs shown in Figures 14 through 17 repeat the time series graphs for MAC and MSC SDT tonnage shipped to both USAFE and PACAF. Using these graphs and the ACFs and PACFs computed with the TIMES forecasting software package, any underlying patterns in the history of the time series were identified. The ACFs and PACFs are located in Appendix C.

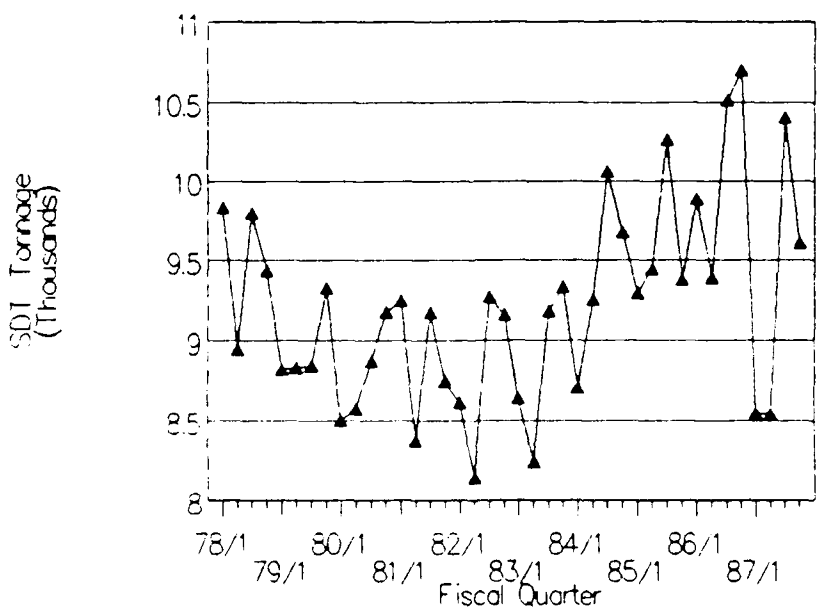


Figure 14. Quarterly SDT Tonnage Shipped to USAFE by MAC

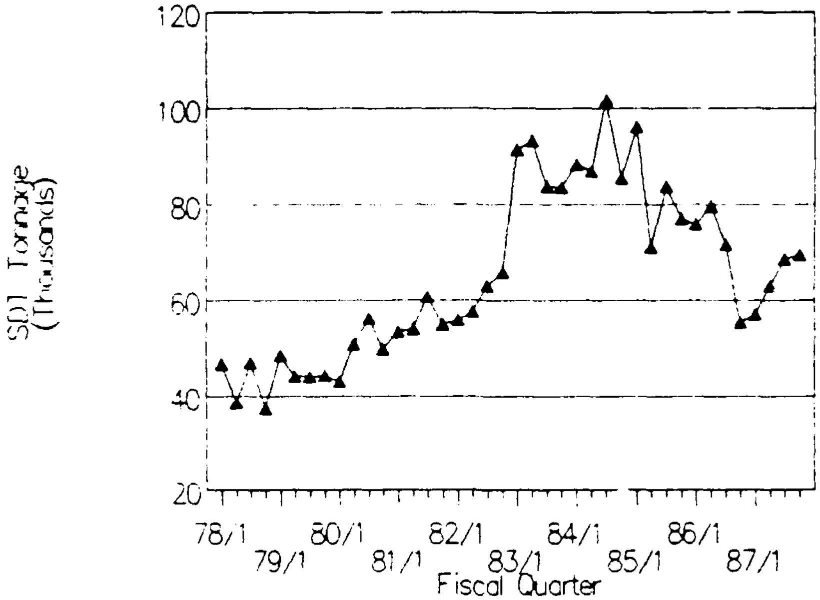


Figure 15. Quarterly SDT Tonnage Shipped to USAFE by MSC

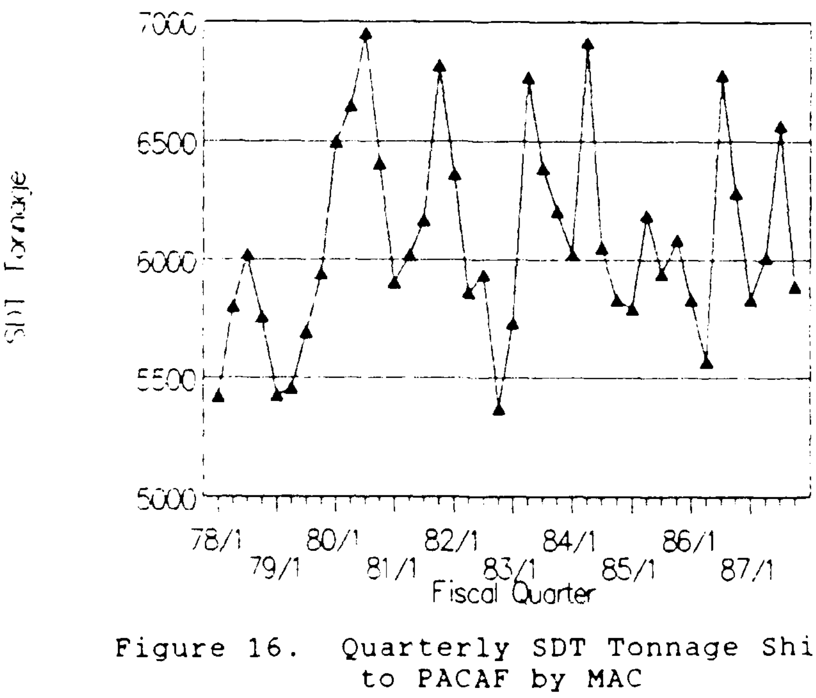


Figure 16. Quarterly SDT Tonnage Shipped to PACAF by MAC

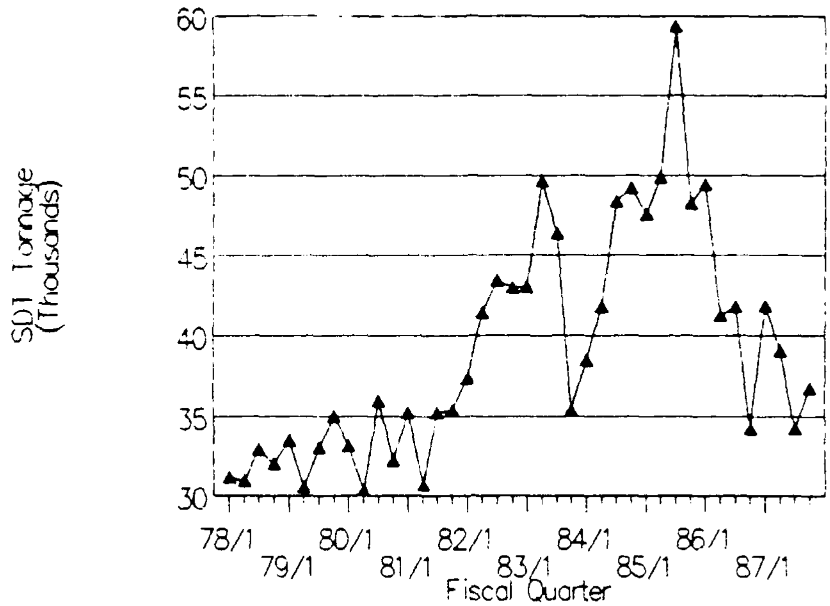


Figure 17. Quarterly SDT Tonnage Shipped to PACAF by MSC

All the graphs, with the exception of the MAC SDT tonnage shipped to PACAF, exhibit some form of nonstationarity. This nonstationarity implied that when constructing the models some degree of differencing was necessary to make the data stationary.

In referring to Appendix C, the ACF and PACF for MAC SDT tonnage shipped to USAFE indicated a need to difference the data. The degree of differencing required was determined by comparing the value "to test whether this series is white noise" (sometimes referred to as the Q-statistic) for the original series to the two differenced series. Since the value for the original series, 44.98, was larger than the values for the other two series (44.14 and

35.63), differencing of order two was conducted. The ACF and PACF for the two difference series were used to determine what parameters should be included in the model. Since significant spikes were apparent in both functions, AR and MA parameters were included.

The ACF and PACF for MSC SDT tonnage shipped to USAFE indicated a need to difference. In comparing the Q-statistic for the original series to the two differenced series, the value for the original series, 177.28, was larger than both the values for the remaining two series (28.78 for one difference and 58.16 for two differences). Since the one difference series possessed the smallest Q-statistic, differencing of order one was conducted in building the model for this data set. The ACF and PACF for the one difference series were used to determine what parameters should be included in the model. Since significant spikes were evident in both functions at the first lag, AR and MA parameters were included.

The ACF and PACF for MAC SDT tonnage shipped to PACAF indicated no need to difference. The Q-statistic for the original series, 15.86, was smaller than the values for the remaining two series (15.99 and 19.27). The ACF and PACF for the original series were used to determine what parameters should be included in the model. Since there was a significant spike in the ACF and the PACF tailed off, only an MA parameter was included.

The ACF and PACF for MSC SDT tonnage shipped to PACAF indicated a need to difference. The Q-statistic for the original, 113.48, was larger than the values for the remaining two series (19.98 and 44.49). The ACF and PACF for the one difference series were used to determine what parameters should be included in the model. Since there were significant spikes in the ACF and the PACF, AR and MA parameters were included.

Model Specification. Using the information gathered in the pattern identification phase, appropriate models were specified. Again, keeping in mind that the BJ model building process is iterative, Equations (30) through (33) present the final models selected.

Equation (30) shows the ARIMA (1,2,2) model used for MAC SDT tonnage shipped to USAFE.

$$Y_t = Y_{t-2} + \Phi_2(Y_{t-2} - Y_{t-4}) - \Theta_1 e_{t-1} - \Theta_2 e_{t-2} + e_t \tag{30}$$

where: Y_t = the forecasted time series values
Y_{t-i} = historical value of the time series
Φ_i = the AR parameter at period i
Θ_i = the MA parameter at period i
e_{t-i} = the error associated with period t - i.

This model accounted for the need to difference the original data set twice. The model also used the patterns associated with the ACF and PACF. The MA parameters included in the model were deemed necessary due to the two signifi nt spikes at lags one and two in the ACF, and the AR parameter was included to account for the significant spike at lag three in the PACF.

Equation (31) presents the ARIMA (1,1,1) model associated with the MSC SDT tonnage shipped to USAFE.

$$Y_t = Y_{t-1} + \Phi_1(Y_{t-1} - Y_{t-2}) - \Theta_1 e_{t-1} + e_t \qquad (31)$$

where: Y_t = the forecasted time series values
Y_{t-i} = historical value of the time series
Φ_i = the AR parameter at period i
Θ_i = the MA parameter at period i
e_{t-i} = the error associated with period t - i.

This model accounted for the need to difference the original data once. It also utilized the appropriate parameters to coincide with the ACF and PACF. The MA parameter was included to account for the major significant spike at lag one in the ACF. The AR parameter was used to explain the large spike at lag one in the PACF.

The ARIMA (0,0,1) model in equation (32) was used with the data for MAC SDT tonnage shipped to PACAF.

$$Y_t = e_t - \Theta_1 e_{t-1} + \mu \qquad (32)$$

where: Y_t = the forecasted time series values
Θ_i = the MA parameter at period i
e_{t-i} = the error associated with period t - i
μ = the mean of the time series.

The model in equation (32) accounted for the necessary patterns identified in the data plot, ACF, and PACF. Only the one MA parameter was included to account for the significant spike at lag one in the ACF and the tailing-off of the PACF.

The ARIMA (1,1,2) model in equation (33) was used for MSC SDT tonnage shipped to PACAF.

$$Y_t = Y_{t-1} + \Phi_1(Y_{t-1} - Y_{t-2}) - \Theta_3 e_{t-3} - \Theta_4 e_{t-4} + e_t \tag{33}$$

where: Y_t = the forecasted time series values
Y_{t-i} = historical value of the time series
Φ_i = the AR parameter at period i
Θ_i = the MA parameter at period i
e_{t-i} = the error associated with period t - i.

This model accounted for the need to difference and the necessary patterns identified previously in the time series. The two MA parameters were used to explain the spikes at lags three and four in the ACF, while the AR parameter was used to account for the spike at lag one in the PACF.

The estimated parameters and models are in Equations (34) through (37) located in the New Model Forecasts section below.

Diagnostic Testing. Eight diagnostic tests were conducted on each of the four specified models. These tests were conducted using TIMES. The necessary output from TIMES concerning these tests is located in Appendix D. As stated earlier in the methodology chapter, the BJ model building process is iterative. Therefore, more than one model for each data set was specified. The results of the diagnostic tests for each of the models for each data set were compared to each other. Only the diagnostic results from the models chosen for each data set are discussed below.

The diagnostic output for MAC SDT tonnage to USAFE showed the following:

1. The mean of the residuals was 47.86 and the standard error remained constant compared to the other models that were specified for this time series.

2. The residual ACF showed only a small "spike" at the third lag, indicating that not all of the disturbance in the time series was accounted for by the specified model.

3. The Q-statistic was 8.276 and when compared with a chi-square variable with 21 degrees of freedom, the associated alpha (α) value fell between 99 and 99.5 percent. Thus, it was concluded with 99 to 99.5 percent confidence, that the residual autocorrelations were not significant implying that the model accounted for all of the significant disturbance in the time series.

4. The cumulative periodogram of the residuals was approximately linear and remained within the expected probability limits, thus implying that the residuals were normalized about a mean of zero.

5. The histogram of the residuals showed a mound-shaped graph centered about zero, implying the residuals met the standard assumption of the error term -- being normalized and centered about a mean of zero.

6. The SSE was 13,133,000 and the MSE was 397,980. These values when compared to similar SSE and MSE values of

other models specified for this data set at 33 degrees of freedom were smaller and therefore more acceptable.

7. The Power Spectrum was horizontal and comparatively smooth. This finding indicated no problems with the error term in the model.

8. The Schwarz statistic, or Bayesian Information Criterion (BIC), was equal to 17,318,826 and was smaller than the BIC for the other models specified for this time series, implying that the model selected was the best fitting.

The diagnostic output for MSC SDT tonnage to USAFE showed the following:

1. The mean of the residuals was 834.31 and the standard error remained constant compared to the other models that were specified for this time series. The mean was large, but acceptable based on the original time series being in the tens of thousands.

2. The residual ACF showed no spikes, indicating the model specified accounted for all the patterns in the time series.

3. The Q-statistic was 13.505 and when compared with a chi-square variable with 22 degrees of freedom, the associated alpha (α) value fell between 90 and 95 percent Thus, it was concluded with 90 to 95 percent confidence, that the residual autocorrelations were not significant

implying that the model accounted for all of the significant disturbance in the time series.

4. The cumulative periodogram of the residuals was approximately linear and remained within the expected probability limits, thus implying that the residuals were normalized about a mean of zero.

5. The histogram of the residuals showed a mound-shaped graph centered about zero, implying the residuals met the standard assumption of the error term -- being normalized and centered about a mean of zero.

6. The SSE was 2,591,500,000 and the MSE was 71,987,000. These values when compared to similar SSE and MSE values of other models specified for this data set at 36 degrees of freedom were smaller and therefore more acceptable.

7. The Power Spectrum was horizontal and relatively smooth. This finding indicated no problems with the error term in the model.

8. The BIC was equal to 3,116,407,298 and was smaller than the BIC for the other models specified for this time series, implying that the model selected was the best fitting.

The diagnostic output for MAC SDT tonnage to PACAF showed the following:

1. The mean of the residuals was 6.5003 and the standard error remained constant compared to the other

models that were specified for this time series.

2. The residual ACF showed no spikes, indicating the model specified accounted for all the patterns in the time series.

3. The Q-statistic was 9.4246 and when compared with a chi-square variable with 22 degrees of freedom, the associated alpha (α) value fell between 99 and 99.5 percent. Thus, it was concluded with 99 to 99.5 percent confidence, that the residual autocorrelations were not significant implying that the model accounted for all of the significant disturbance in the time series.

4. The cumulative periodogram of the residuals was linear and remained within the expected probability limits, thus implying that the residuals were normalized about a mean of zero.

5. The histogram of the residuals showed a mound-shaped graph centered about zero, implying the residuals met the standard assumption of the error term -- being normalized and centered about a mean of zero.

6. The SSE was 6,011,300 a the MSE was 158,190. These values when compared to similar SSE and MSE values of other models specified for this data set at 38 degrees of freedom were smaller and therefore more acceptable.

7. The Power Spectrum was horizontal and smooth. This finding indicated no problems with the error term in the model.

8. The BIC was equal to 6,592,041 and was smaller than the BIC for the other models specified for this time series, implying that the model selected was the best fitting.

The diagnostic output for MSC SDT tonnage to PACAF showed the following:

1. The mean of the residuals was 172.20 and the standard error remained constant compared to the other models that were specified for this time series. The mean was large, but acceptable based on the original series being in the tens of thousands.

2. The residual ACF showed no spikes, indicating the model specified accounted for all the patterns in the time series.

3. The Q-statistic was 11.469 and when compared with a chi-square variable with 21 degrees of freedom, the associated alpha (α) value fell between 95 and 97.5 percent. Thus, it was concluded with 95 to 97.5 percent confidence, that the residual autocorrelations were not significant implying that the model accounted for all of the significant disturbance in the time series.

4. The cumulative periodogram of the residuals was approximately linear and remained within the expected probability limits, thus implying that the residuals were normalized about a mean of zero.

5. The histogram of the residuals showed a mound-shaped graph centered about zero, implying the residuals met

the standard assumption of the error term -- being normalized and centered about a mean of zero.

6. The SSE was 735,760,000 and the MSE was 21,022,000. These values when compared to similar SSE and MSE values of other models specified for this data set at 35 degrees of freedom were smaller and therefore more acceptable.

7. The Power Spectrum was horizontal and smooth. This finding indicated no problems with the error term in the model.

8. The BIC was equal to 970,265,687 and was smaller than the BIC for the other models specified for this time series, implying that the model selected was the best fitting.

These diagnostic tests confirmed that the BJ models chosen for forecasting the four time series were statistically valid and the most acceptable models of those specified.

New Model Forecasts. After the specified models passed the diagnostic tests with stability, forecasts were conducted for FY 88/1 through FY 89/2.

The ARIMA (1,2,2) model used to forecast MAC SDT tonnage to USAFE is expressed in equation (34). The equation includes the numerical parameters.

$$Y_t = Y_{t-2} - 0.50572(Y_{t-2} - Y_{t-4}) - 1.4292e_{t-1} + 0.73174e_{t-2} + e_t \qquad (34)$$

The ARIMA (1,1,1) model including the numerical parameters used to forecast MSC SDT tonnage to USAFE is shown in equation (35).

$$Y_t = Y_{t-1} - 0.809(Y_{t-1} - Y_{t-2}) + 0.5753e_{t-1} + e_t \tag{35}$$

MAC SDT tonnage shipped to PACAF was forecasted using the ARIMA (0,0,1) model expressed in equation (36).

$$Y_t = e_t + 0.40823e_{t-1} + 6064.4 \tag{36}$$

The ARIMA (1,1,2) model shown in equation (37) was used to forecast MSC SDT tonnage to PACAF.

$$\begin{aligned} Y_t &= Y_{t-1} - 0.26403(Y_{t-1} - Y_{t-2}) \\ &- 0.074567e_{t-3} + 0.18636e_{t-4} = e_t \end{aligned} \tag{37}$$

The forecasted values for each of these time series are shown in Table 5. These can be compared with the AFLC/DSXR forecasts in Table 4 and the actual tonnage in Appendix A.

Table 5

Box-Jenkins Forecasted Values for SDT Tonnage

	MAC SDT		MSC SDT	
FY	USAFE	PACAF	USAFE	PACAF
88/1	8,516	5,909	70,021	37,004
88/2	8,631	6 064	69,589	37,380
88/3	8,890	6,064	69,939	36,098
88/4	8,542	6,064	69,656	36,939
89/1	8,121	6,064	69,885	36,717
89/2	8,007	6,064	69,700	36,776

Accuracy Measurement. As discussed in Chapter III, the mean absolute percent error (MAPE) was used to measure the accuracy of AFLC/DSXR's forecasting model and the BJ models built during this research. The forecast errors for AFLC/DSXR's models were computed by subtracting the actual SDT tonnage from the forecasts. Likewise, the errors for the BJ models developed in this research were computed by subtracting the actual tonnage from the predictions. Table 6 includes the MAPE for each of the models.

Table 6

MAPE Evaluations of the Forecast Models

	MAC SDT		MSC SDT	
Model	USAFE	PACAF	USAFE	PACAF
AFLC/DSXR	32.95	35.40	6.61	7.87
AFLC/DSXR (in tons)	3,037	2,151	4,295	3,085
Box-Jenkins	19.31	33.25	6.97	18.85
Box-Jenkins (in tons)	1,780	2,021	4,529	7,389

The tonnage values in Table 6 are the absolute error in tonnage. In effect, they are the percentage of the average tonnage shipped for that particular data set.

Summary

This chapter presented the results and analysis of this research. These results allowed for the findings and implications, included in Chapter V, to be drawn. These findings and implications are based solely on the results and analysis of this research.

V. Findings and Implications

This chapter is devoted to the discussion of the findings resulting from this research and the implications of these findings on the forecasting of AFLC SDT tonnage.

Findings

Research Objective 1. Validate the current forecasting method used for computing tonnage estimates to derive SDT budget requests.

As stated in Chapter IV, this research objective was accomplished by data analysis and a 3-step model validation process.

Data Analysis. The findings from graphically analyzing the four data sets were that none of these sets were entirely appropriate for use with linear regression. Graphing the SDT tonnage versus flying hours showed all four sets were curvilinear, cone-shaped, or blocked, and therefore inappropriate for use with linear regression. In addition, when SDT tonnage was graphed as a time series, the same findings were reached. The data in these four sets did not lend themselves for use with linear regression.

Current Model Validation. The findings from the 3-step model validation process were varied. All flying hour parameter confidence intervals for MAC SDT tonnage shipped to both USAFE and PACAF overlapped. There were, however, several parameter confidence intervals failed to overlap for MSC SDT tonnage shipped to USAFE and PACAF.

Based on these failures, the null hypothesis that the parameters were stable after each regression was rejected. The iterative regression process utilized by AFLC/DSXR to predict MSC SDT tonnage shipped to both USAFE and PACAF was therefore statistically invalidated based on a 95 percent confidence level. This means that H_0 was rejected as being false with only a five percent chance of rejecting H_0 and it being true. This research, however, resulted in a failure to reject the null hypothesis for predicting MAC SDT tonnage shipped to USAFE and PACAF.

The varying number of quarters used in each regression also contributed to the instability of the model. Although the regressions for MSC SDT tonnage shipped to USAFE and PACAF used 40 quarters and were therefore in the more stable range of the confidence interval graphs, the regressions for MAC SDT tonnage shipped to USAFE and PACAF fell in the more unstable ranges. The regressions for MAC SDT tonnage shipped to USAFE and PACAF used 20 and 23 quarters respectively. These two regressions fell in the confidence interval ranges where the intervals began increasing in size to account for the same probability of the parameter values falling within the interval limits. In addition, it was in these ranges where the intervals began to fluctuate more widely and become unstable. This increase in range size implies that larger degrees of error are necessary in order for the confidence interval to include the actual tonnage value, based on a 95 percent confidence level.

In summary, this first research objective was met in that the current method was statistically invalidated. It is evident, based on a 95 percent confidence level, that the flying hour parameters for the MSC SDT data sets are in fact unstable after certain regressions used during AFLC/DSXR's iterative forecasting method. This finding undoubtedly casts suspicion on the method, in general, as a forecasting tool.

Research Objective 2. **If the current method's validity was not supported, develop a new forecasting model, using the same input data, that would produce more accurate and reliable tonnage estimates.**

This research objective, as stated earlier, was accomplished in two steps. First, Box-Jenkins (BJ) time series forecasting models were built for each of the four data sets. Secondly, the accuracy of these models was evaluated and compared to that of the current model using the mean absolute percent error (MAPE).

Model Building. In building BJ models for each of these four times series, the 4-step BJ model building process, discussed in Chapter III, was conducted. The results were four separate ARIMA models, one for each time series. These ARIMA models, built using patterns identified in the history of the time series, were then used to forecast SDT tonnage for FY 88/1 through FY 89/2.

Accuracy Measurement. The forecasts made using these newly developed BJ models were compared to AFLC/DSXR's forecasts using the MAPE. The results of this comparison were varied and are included previously in Table 6.

The MAPE from the BJ model forecast for MAC SDT tonnage shipped to both USAFE and PACAF were smaller than the MAPE for the AFLC/DSXR models. These were the two data sets where the AFLC/DSXR method could not be statistically invalidated. This supports the fact that the BJ models developed for these data sets provide more accurate forecasts than the "valid" AFLC/DSXR models. The MAPE from the BJ model forecast for MSC SDT tonnage shipped to USAFE and PACAF were larger than those for the AFLC/DSXR models. The BJ models for these two data sets are, however, valid models, whereas the AFLC/DSXR method used for the same data sets was statistically invalidated.

The first finding above met the research objective of developing a new forecasting model that was a more accurate predictor of SDT tonnage than the current model. The MAPE values, however, were large (19.31 percent for MAC SDT tonnage forecast for USAFE and 33.25 percent for MAC SDT tonnage forecast for PACAF) in relation to the mean value of each corresponding time series. These values imply that the mean absolute error of the forecast is 19.31 percent of the mean actual tonnage for the MAC SDT tonnage shipped to USAFE, and 33.25 percent of the mean actual tonnage for the MAC SDT tonnage shipped to PACAF. These values translate into 1,780 and 2,021 short tons for the respective time series. Yet, even with these relatively large MAPE values, the BJ models developed are more accurate in predicting future values of these two time series than the AFLC/DSXR models which yield errors of 3,037 and 2,151 short tons respectively.

One final note here is that the AFLC/DSXR models for these two time series were not statistically invalidated during this research and were therefore considered "valid" models based on the 95 percent confidence level chosen for this research. It is therefore an important finding that the BJ models developed for these time series were more accurate than the "valid" AFLC/DSXR models for the same series.

The second finding noted above that the BJ MAPE values for the two MSC SDT time series were larger than the corresponding MAPE values for the AFLC/DSXR models was attributed to the "naiveté" of the BJ time series modeling process. Due to SDT funding cuts, MAC SDT shipments were diverted to MSC SDT shipments causing unexpected increases in the MSC SDT shipments between FY 88/1 and FY 89/2. The BJ process uses history of a time series to forecast the future of that time series and was therefore unable to detect or predict these increases. Even though the BJ models developed for these two MSC SDT time series were less accurate than the AFLC/DSXR models for the same series based on the MAPE values, they were both relatively accurate. The BJ MAPE values (6.97 for MSC SDT tonnage forecast for USAFE and 18.85 for MSC SDT tonnage forecast for PACAF) imply that the mean absolute error is 6.97 percent of the mean actual MSC SDT tonnage shipped to USAFE, and 18.85 percent of the mean actual MSC SDT tonnage shipped to PACAF. These values translate into 4,529 and 7,389 measurement tons for the respective time series. The values are relatively small forecast errors considering the average tonnage shipped for the 40 quarters in the time series was 64,980 and 39,198 measurement tons respectively.

One final note here is that although the AFLC/DSXR models for these two time series were more accurate than the BJ models developed for these same series, these two AFLC/DSXR models were the two that were statistically invalidated during this research. Therefore, a choice must be made between a statistically invalid model that is marginally more accurate or a statistically valid model that is marginally less accurate.

In summary, this second research objective was met by developing the appropriate BJ models. The BJ models for the two MAC SDT time series were more accurate than the

AFLC/DSXR models for the same series based on the MAPE. The BJ models developed for the two MSC SDT time series, although marginally less accurate than the AFLC/DSXR models for the same series, were valid models, whereas the AFLC/DSXR models were statistically invalidated during the course of this research.

Implications

The results presented here offer some valuable insight into the management of the AFLC SDT budget forecasting process.

Continual Analysis and Updating. Although the SDT tonnage data sets evaluated in this research may have been linear in the early 1970's when AFLC/DSXR's model was built, that is not the case at the present time. Forecasting inputs and outputs must be continually analyzed and updated according to the current conditions of the data being forecasted. Using a forecasting method inappropriate for a particular data set serves no purpose and usually provides inaccurate results. AFLC/DSXR has used the same iterative linear regression model for the past several years. It is apparent, however, by reviewing the plots of the data in Chapter IV that there are no linear relationships. AFLC/DSXR's current approach is therefore inappropriate for the data sets it forecasts.

Accurate Model Need. The need for an accurate and statistically valid forecasting model to predict SDT tonnage is necessary as a result of AFLC/DSXR's current model being statistically invalidated in this research. Based on the fact that there are external factors affecting these time series such as the diversion of cargo from air to sea movement and the delay of some shipments, self-projecting methods (i.e. Box-Jenkins) become less effective. Econometric models are more apt to detect these external effects and therefore become better predictors of such time series.

Data Base Size Increase. Any forecasting method whether linear regression, Box-Jenkins, or econometric requires a vast amount, usually at least 50 to 60 periods, of historical data. The amount of data (40 quarters) used in this research, although statistically acceptable, was limited. Ideally, 50 to 60 periods (for this research, quarters) should be used to more accurately forecast any given time series. This implication would require AFLC/DSXR to retain 13 to 15 years of data rather than ten. Alternatively, monthly data for four to five years could be used. If, however, an econometric model was employed, additional data bases would be needed for the new independent variables (i.e. manpower, weapon system).

Further Research. As with most research, a final and definitive answer is rarely reached, and this thesis proved no different.

The research conducted in this thesis effort only "opened the door" to finding a significantly accurate and valid model for predicting SDT tonnage. In statistically invalidating AFLC/DSXR's current model, this research has caused an immediate need for an accurate and valid model. Further research in this area, particularly in econometric models as discussed above, would prove beneficial. By employing a model with other independent variables such as manpower, weapon system type, etc., as well as variables to predict the unexpected increases or decreases in tonnage caused by diversions, a significantly more accurate model could be developed. Another advantage of econometric models is the ability to engage in simulation of potential changes to assess their impact on SDT budget requirements.

Another aspect that may be worth pursuing is to use monthly data instead of quarterly data. In utilizing monthly data, AFLC/DSXR will have a far greater data base to work with than the one it currently uses. This could improve the accuracy of any forecast.

Further research should also be conducted concerning the idea to further divide the SDT tonnage being forecasted into more definable subcategories such as particular weapon system spare parts (i.e. F-16 spares). This subcategorization, although causing a greater number of forecasts to be conducted, may allow for more accurate estimates of SDT tonnage.

Appendix A: SDT Tonnage and Flying Hour Data

SDT Tonnage Shipped to USAFE by MAC

Quarter	SDT Tons	Flying Hours
78/1	9,828	57,480
/2	8,942	52,034
/3	9,793	64,399
/4	9,430	69,807
79/1	8,821	55,423
/2	8,831	56,900
/3	8,841	71,221
/4	9,322	71,846
80/1	8,496	60,461
/2	8,573	58,808
/3	8,867	69,735
/4	9,174	68,069
81/1	9,244	63,546
/2	8,372	65,588
/3	9,170	75,263
/4	8,747	75,477
82/1	8,610	61,878
/2	8,138	70,025
/3	9,270	80,973
/4	9,153	78,365
83/1	8,637	66,217
/2	8,242	70,496
/3	9,178	77,627
/4	9,327	77,944
84/1	8,704	69,485
/2	9,249	73,093
/3	10,058	78,651
/4	9,672	77,702
85/1	9,289	69,027
/2	9,439	70,119
/3	10,259	83,336
/4	9,377	79,858
86/1	9,887	75,552
/2	9,383	74,412
/3	10,508	80,673
/4	10,700	77,628
87/1	8,551	75,308
/2	8,538	71,368
/3	10,402	87,519
/4	9,602	81,329
88/1	9,774	73,531
/2	8,254	71,959
/3	6,996	79,331
/4	6,848	83,366
89/1	7,538	77,571
/2	5,765	77,597

SDT Tonnage Shipped to USAFE by MSC

Quarter	SDT Tons	Flying Hours
78/1	46,778	57,480
/2	38,450	52,034
/3	47,078	64,399
/4	37,450	69,807
79/1	48,574	55,423
/2	44,156	56,900
/3	44,041	71,221
/4	44,296	71,846
80/1	42,971	60,461
/2	50,901	58,808
/3	56,271	69,735
/4	49,844	68,069
81/1	53,377	63,546
/2	53,945	65,588
/3	60,785	75,263
/4	54,941	75,477
82/1	55,855	61,878
/2	57,543	70,025
/3	63,076	80,973
/4	65,851	78,365
83/1	91,436	66,217
/2	93,263	70,496
/3	83,737	77,627
/4	83,617	77,944
84/1	88,315	69,485
/2	86,968	73,093
/3	101,701	78,651
/4	85,521	77,702
85/1	96,200	69,027
/2	71,083	70,119
/3	83,702	83,336
/4	77,001	79,858
86/1	75,830	75,552
/2	79,563	74,412
/3	71,583	80,673
/4	55,248	77,628
87/1	57,088	75,308
/2	63,014	71,368
/3	68,675	87,519
/4	69,487	81,329
88/1	70,569	73,531
/2	70,459	71,959
/3	81,479	79,331
/4	76,619	83,366
89/1	73,511	77,571
/2	62,455	77,597

SDT Tonnage Shipped to PACAF by MAC

Quarter	SDT Tons	Flying Hours
78/1	5,421	35,287
/2	5,801	37,575
/3	6,021	34,865
/4	5,754	35,922
79/1	5,427	35,310
/2	5,456	37,593
/3	5,692	35,600
/4	5,940	35,615
80/1	6,495	35,622
/2	6,647	37,403
/3	6,951	36,133
/4	6,406	34,429
81/1	5,902	36,236
/2	6,016	35,292
/3	6,166	36,480
/4	6,818	36,718
82/1	6,363	36,194
/2	5,860	37,007
/3	5,934	38,635
/4	5,368	37,534
83/1	5,729	37,293
/2	6,768	39,678
/3	6,386	39,129
/4	6,203	37,617
84/1	6,020	40,018
/2	6,916	40,533
/3	6,050	39,523
/4	5,829	38,235
85/1	5,792	40,802
/2	6,188	40,828
/3	5,938	41,344
/4	6,084	40,983
86/1	5,829	42,905
/2	5,569	41,942
/3	6,782	41,476
/4	6,285	41,372
87/1	5,830	44,270
/2	6,008	42,322
/3	6,566	44,381
/4	5,886	43,700
88/1	5,835	42,588
/2	5,582	41,962
/3	4,787	42,206
/4	3,906	42,255
89/1	3,850	42,856
/2	4,039	43,482

SDT Tonnage Shipped to PACAF by MSC

Quarter	SDT Tons	Flying Hours
78/1	31,163	35,287
/2	30,967	37,575
/3	32,924	34,865
/4	32,018	35,922
79/1	33,469	35,310
/2	30,548	37,593
/3	33,046	35,600
/4	34,991	35,615
80/1	33,145	35,622
/2	30,312	37,403
/3	35,918	36,133
/4	32,220	34,429
81/1	35,198	36,236
/2	30,649	35,292
/3	35,193	36,480
/4	35,396	36,718
82/1	37,343	36,194
/2	41,379	37,007
/3	43,392	38,635
/4	42,968	37,534
83/1	43,039	37,293
/2	49,651	39,678
/3	46,352	39,129
/4	35,398	37,617
84/1	38,462	40,018
/2	41,800	40,533
/3	48,352	39,523
/4	49,203	38,235
85/1	47,567	40,802
/2	49,835	40,828
/3	59,435	41,344
/4	48,235	40,983
86/1	49,398	42,905
/2	41,209	41,942
/3	41,782	41,476
/4	34,195	41,372
87/1	41,814	44,270
/2	39,046	42,322
/3	34,185	44,381
/4	36,701	43,700
88/1	42,387	42,588
/2	48,394	41,962
/3	55,113	42,206
/4	42,250	42,255
89/1	42,513	42,856
/2	44,280	43,482

Appendix B: Flying Hour Parameter Confidence Interval Values

SDT Tonnage Shipped to USAFE by MAC

# of Quarters	Lower Limit	Parameter	Upper Limit
40	0.0173	0.0385	0.0598
39	0.0241	0.0449	0.0658
38	0.0283	0.0507	0.0732
37	0.0326	0.0544	0.0763
36	0.0329	0.0549	0.0769
35	0.0368	0.0604	0.0839
34	0.0416	0.0668	0.0920
33	0.0410	0.0665	0.0920
32	0.0405	0.0667	0.0929
31	0.0398	0.0681	0.0964
30	0.0417	0.0731	0.1044
29	0.0405	0.0728	0.1051
28	0.0417	0.0751	0.1084
27	0.0508	0.0852	0.1195
26	0.0469	0.0839	0.1210
25	0.0461	0.0839	0.1218
24	0.0463	0.0840	0.1217
23	0.0497	0.0931	0.1365
22	0.0421	0.0859	0.1297
21	0.0465	0.0909	0.1354
20	0.0484	0.0932	0.1380
19	0.0441	0.0951	0.1460
18	0.0333	0.0849	0.1364
17	0.0339	0.0859	0.1380
16	0.0339	0.0872	0.1404
15	0.0225	0.0814	0.1402
14	0.0171	0.0803	0.1434
13	0.0131	0.0792	0.1453
12	0.0090	0.0792	0.1494
11	0.0049	0.0881	0.1713
10	0.0068	0.1061	0.2053
9	-0.0109	0.1047	0.2204
8	-0.0156	0.1096	0.2347

SDT Tonnage Shipped to USAFE by MSC

# of Quarters	Lower Limit	Parameter	Upper Limit
40	0.5329	1.1275	1.7220
39	0.4869	1.1117	1.7365
38	0.3729	1.0607	1.7484
37	0.3165	1.0188	1.7210
36	0.3045	0.9868	1.6692
35	0.2165	0.9641	1.7116
34	0.0530	0.8703	1.6876
33	0.0370	0.8390	1.6411
32	0.0257	0.8157	1.6057
31	-0.1867	0.6469	1.4805
30	-0.4271	0.4973	1.4216
29	-0.4982	0.4397	1.3775
28	-0.6272	0.3146	1.2565
27	-0.8906	0.1078	1.1063
26	-1.1546	-0.1202	0.9141
25	-1.1592	-0.1219	0.9153
24	-1.1324	-0.1190	0.8945
23	-1.7070	-0.6126	0.4819
22	-1.9169	-0.8562	0.2046
21	-1.8531	-0.7614	0.3303
20	-1.8197	-0.7125	0.3947
19	-1.8447	-0.5923	0.6602
18	-1.7416	-0.4259	0.8898
17	-1.7966	-0.4409	0.9147
16	-1.8650	-0.4636	0.9379
15	-1.8387	-0.2957	1.2473
14	-1.8011	-0.1787	1.4437
13	-1.6941	-0.2887	1.1167
12	-1.7191	-0.3073	1.1045
11	-0.8706	0.3870	1.6447
10	-0.9931	0.5492	2.0914
9	-1.3638	0.2371	1.8380
8	-1.5351	0.1530	1.8411

SDT Tonnage Shipped to PACAF by MAC

# of Quarters	Lower Limit	Parameter	Upper Limit
40	-0.0360	0.0126	0.0612
39	-0.0430	0.0058	0.0545
38	-0.0445	0.0047	0.0539
37	-0.0473	0.0038	0.0550
36	-0.0520	0.0002	0.0524
35	-0.0613	-0.0093	0.0428
34	-0.0638	-0.0131	0.0377
33	-0.0716	-0.0202	0.0312
32	-0.0784	-0.0247	0.0290
31	-0.0768	-0.0209	0.0351
30	-0.0732	-0.0168	0.0395
29	-0.0597	-0.0047	0.0503
28	-0.0567	0.0029	0.0625
27	-0.0641	-0.0013	0.0614
26	-0.0734	-0.0048	0.0638
25	-0.0776	-0.0040	0.0695
24	-0.0576	0.0160	0.0895
23	-0.0502	0.0297	0.1097
22	-0.0622	0.0252	0.1126
21	-0.0692	0.0227	0.1147
20	-0.0988	-0.0059	0.0870
19	-0.1326	-0.0313	0.0700
18	-0.1163	-0.0174	0.0815
17	-0.1137	-0.0086	0.0965
16	-0.1290	-0.0024	0.1242
15	-0.1418	-0.0057	0.1303
14	-0.0984	0.0189	0.1362
13	-0.1107	0.0222	0.1550
12	-0.1902	-0.0058	0.1787
11	-0.2322	-0.0307	0.1708
10	-0.2597	-0.0245	0.2106
9	-0.3078	-0.0404	0.2269
8	-0.3912	-0.0536	0.2840

SDT Tonnage Shipped to PACAF by MSC

# of Quarters	Lower Limit	Parameter	Upper Limit
40	0.6074	1.3024	1.9975
39	0.5[illegible]74	1.2609	1.9744
38	0.5230	1.2346	1.9461
37	0.4685	1.2078	1.9470
36	0.4061	1.1621	1.9180
35	0.3447	1.1290	1.9133
34	0.3061	1.0848	1.8636
33	0.2273	1.0326	1.8378
32	0.1535	1.0008	1.8482
31	0.0504	0.9324	1.8144
30	-0.0248	0.8499	1.7245
29	-0.1079	0.8046	1.7172
28	-0.3337	0.6494	1.6325
27	-0.4777	0.5522	1.5821
26	-0.8120	0.2615	1.3351
25	-1.0399	0.0812	1.2023
24	-1.2[illegible]83	-0.1342	1.0299
23	-1.6539	-0.4026	0.8486
22	-1.9044	-0.5466	0.8113
21	-2.0104	-0.5812	0.8481
20	-2.2625	-0.6968	0.8690
19	-2.6618	-0.8925	0.8767
18	-2.6172	-0.7809	1.0554
17	-2.7108	-0.7333	1.2442
16	-3.8217	-1.7134	0.3949
15	-4.1594	-2.0360	0.0875
14	-4.3907	-2.1780	0.0348
13	-4.7401	-2.2334	0.2732
12	-6.3182	-2.8553	0.6076
11	-6.7867	-2.8574	1.0719
10	-7.1545	-2.5967	1.9610
9	-4.9062	-1.2747	2.3568
8	-4.4304	-0.3093	3.8117

Appendix C: Original Series Autocorrelation and Partial Autocorrelation Functions

AUTOCORRELATION FUNCTION

DATA - SDT Tonnage Shipped by MAC to USAFE   40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .92156E+04
ST. DEV. OF SERIES = .60563E+03
NUMBER OF OBSERVATIONS = 40

1- 12	.29	.02	.32	.50	.22	.00	.15	.03	.05	-.00	-.15	.15
ST.E.	.16	.17	.17	.18	.22	.22	.22	.22	.23	.23	.24	.24
13- 24	-.17	-.26	-.11	.05	-.30	-.33	-.16	-.03	-.24	-.26	-.24	-.07
ST.E.	.24	.24	.25	.25	.25	.26	.27	.27	.27	.28	.28	.28

MEAN DIVIDED BY ST. ERROR = .93162E+02

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .44932E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

DIFFERENCE 1
MEAN OF THE SERIES =-.57949E+01
ST. DEV. OF SERIES = .74704E+03
NUMBER OF OBSERVATIONS = 39

1- 12	-.31	-.40	.09	.31	-.03	-.05	.00	.29	-.01	-.23	-.04	.07
ST.E.	.16	.17	.20	.20	.21	.21	.22	.22	.23	.23	.24	.24
13- 24	-.14	-.01	.04	.35	-.22	-.15	.02	.25	-.14	-.18	.17	.03
ST.E.	.25	.25	.26	.26	.27	.27	.28	.28	.28	.28	.29	.29

MEAN DIVIDED BY ST. ERROR = .48443E-01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .44137E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

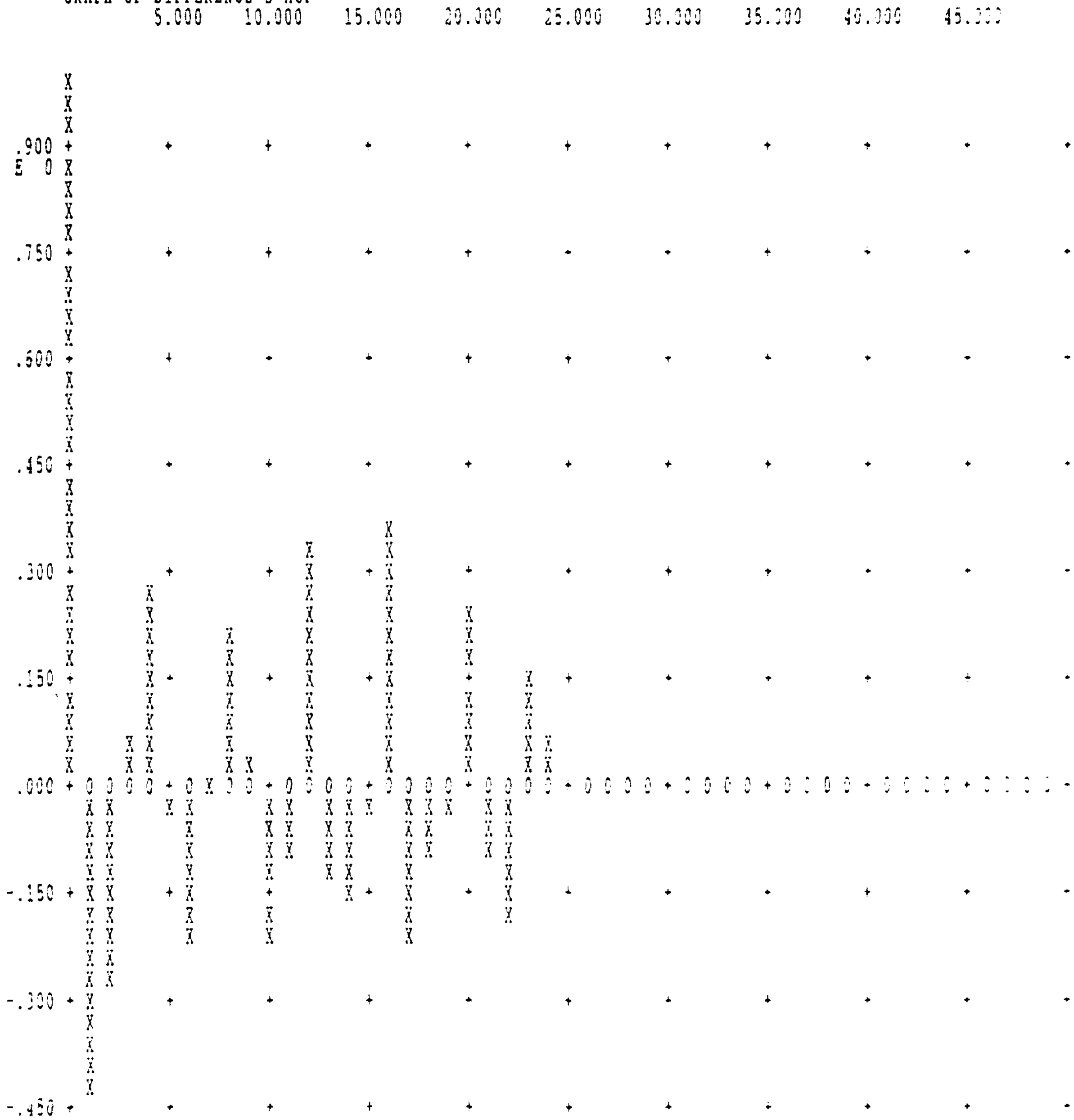
DIFFERENCE 2
MEAN OF THE SERIES = .22632E+01
ST. DEV. OF SERIES = .12090E+04
NUMBER OF OBSERVATIONS = 38

1- 12	-.41	.07	.07	.07	-.03	-.21	-.31	.00	.08	-.21	-.13	.34
ST.E.	.16	.19	.20	.20	.21	.21	.21	.22	.22	.22	.22	.22
13- 24	-.12	-.15	-.04	.36	-.22	-.08	-.03	.25	-.10	-.19	.16	.07
ST.E.	.24	.24	.24	.24	.26	.26	.26	.26	.27	.27	.27	.27

MEAN DIVIDED BY ST. ERROR = .11539E-01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .35607E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

SDT Tonnage Shipped by MAC to USAFE
GRAPH OF DIFFERENCE 2 ACF



PARTIAL AUTOCORRELATIONS

DATA - SDT Tonnage Shipped by MAC to USAFE 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 2

ORIGINAL SERIES
MEAN OF THE SERIES = .92156E+04
ST. DEV. OF SERIES = .62563E+03
NUMBER OF OBSERVATIONS = 40

1- 12	.29	-.07	.36	.37	.07	-.12	-.36	.00	-.11	-.24	-.11	.03
13- 24	-.18	-.01	-.02	.10	-.20	.02	-.13	.07	-.08	.11	.07	-.10

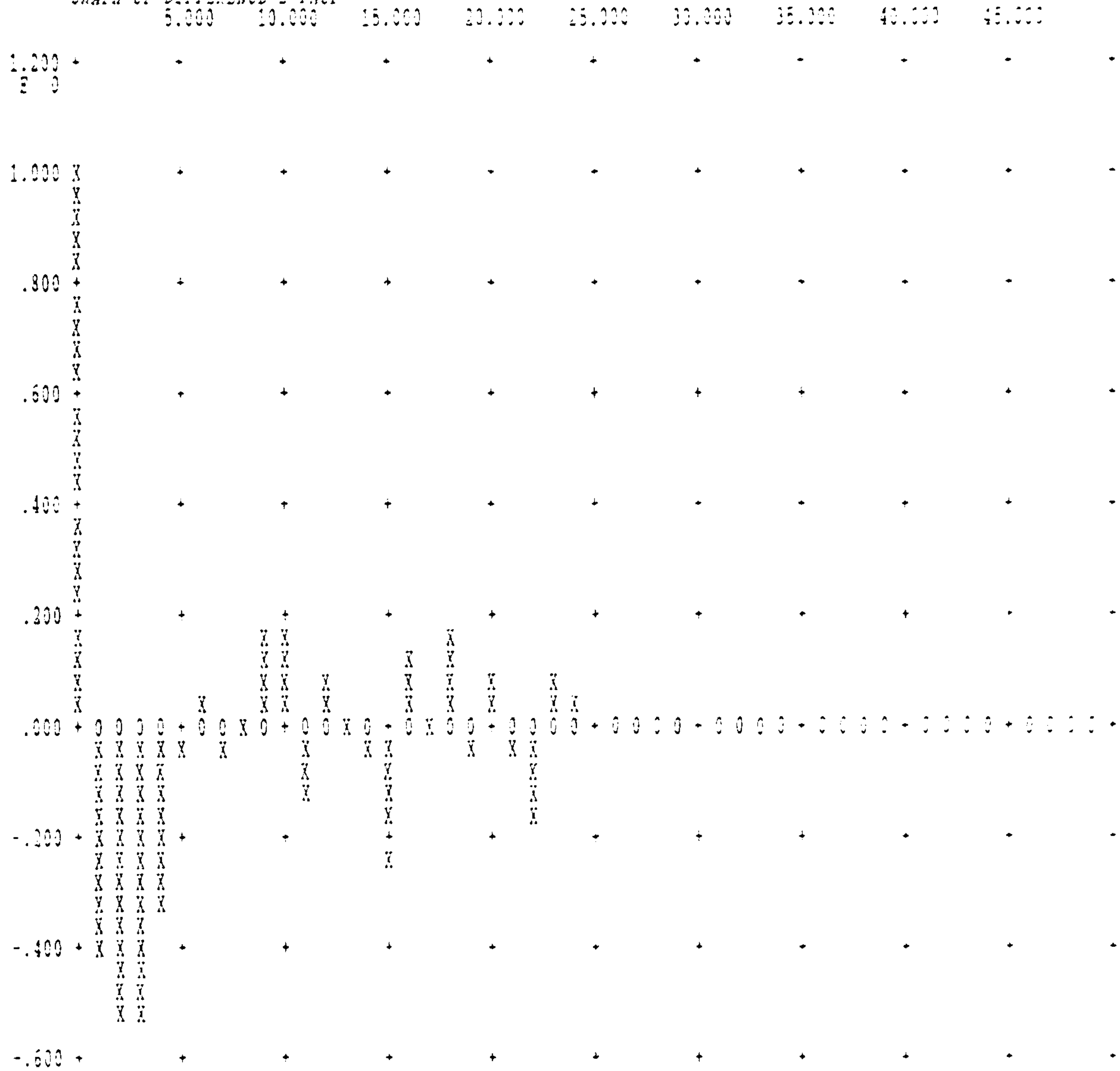
DIFFERENCE 1
MEAN OF THE SERIES =-.57949E+01
ST. DEV. OF SERIES = .71704E+03
NUMBER OF OBSERVATIONS = 39

1- 12	-.31	-.54	-.42	-.09	.10	.03	-.06	.11	.19	.06	-.16	.07
13- 24	-.10	-.10	-.17	.20	.01	.13	-.03	.02	-.13	-.15	.03	-.03

DIFFERENCE 2
MEAN OF THE SERIES = .22632E+01
ST. DEV. OF SERIES = .12090E+04
NUMBER OF OBSERVATIONS = 38

1- 12	-.41	-.53	-.54	-.31	-.04	.04	-.05	.02	.17	.17	-.11	.03
13- 24	-.01	-.03	-.24	.11	.00	.14	-.04	.07	-.04	-.16	.07	.05

SDT Tonnage Shipped by MAC to USAFE
GRAPH OF DIFFERENCE 2 PACF



AUTOCORRELATION FUNCTION

DATA - SDT Tonnage Shipped by MSC to USAFE 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .64980E+05
ST. DEV. OF SERIES = .17731E+05
NUMBER OF OBSERVATIONS = 40

1- 12	.85	.79	.68	.63	.56	.50	.37	.25	.11	.07	[illegible]	[illegible]
ST.E.	.16	.25	.30	.34	.37	.39	.40	.41	.42	.42	.42	.42
13- 24	-.15	-.23	-.31	-.31	-.36	-.38	-.42	-.44	-.41	-.37	-.36	[illegible]
ST.E.	.42	.42	.42	.43	.43	.44	.45	.46	.47	.48	.49	.49

MEAN DIVIDED BY ST. ERROR = .23173E+02

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .17723E-03
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

DIFFERENCE 1
MEAN OF THE SERIES = .58228E+03
ST. DEV. OF SERIES = .92546E+04
NUMBER OF OBSERVATIONS = 39

1- 12	-.38	.25	-.26	.03	-.03	.00	-.04	.10	-.37	[illegible]	[illegible]	[illegible]
ST.E.	.16	.18	.19	.20	.20	.20	.21	.21	.21	[illegible]	[illegible]	[illegible]
13- 24	-.06	.05	-.31	.15	-.10	.08	-.05	-.02	-.01	.04	-.12	[illegible]
ST.E.	.23	.23	.23	.24	.24	.25	.25	.25	.25	.25	.25	.25

MEAN DIVIDED BY ST. ERROR = .39292E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .28783E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

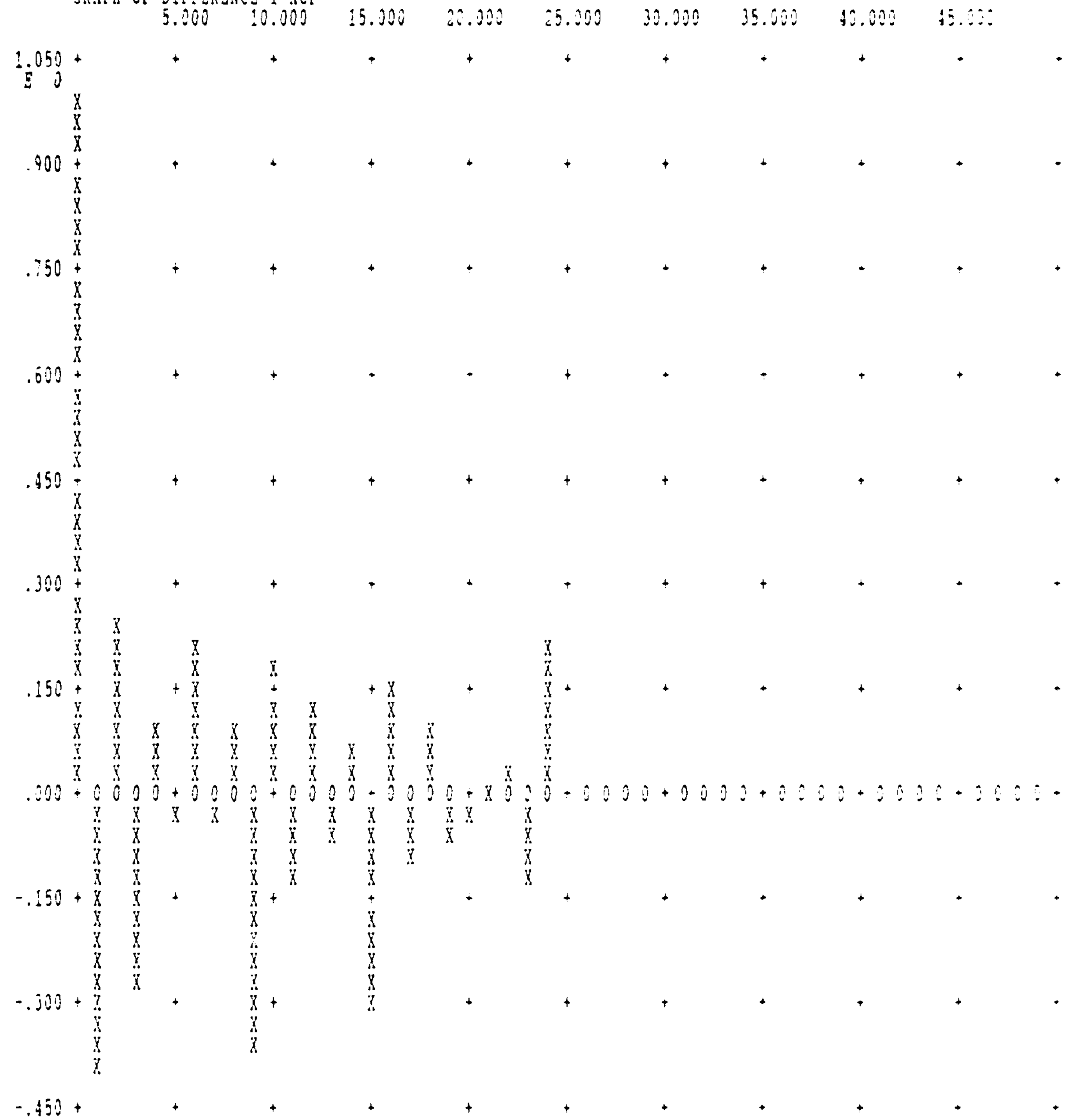
DIFFERENCE 2
MEAN OF THE SERIES = .24053E+03
ST. DEV. OF SERIES = .15534E+05
NUMBER OF OBSERVATIONS = 38

1- 12	-.72	.40	-.29	.15	-.12	[illegible]	-.14	.03	-.38	.30	[illegible]	.15
ST.E.	.16	.23	.25	.26	.26	.26	.26	[illegible]	[illegible]	.29	[illegible]	[illegible]
13- 24	-.10	.16	-.29	.26	-.15	.11	-.04	-.02	-.03	.09	[illegible]	.03
ST.E.	.30	.30	.30	.31	.31	.32	.32	.32	.32	.32	.32	.32

MEAN DIVIDED BY ST. ERROR = .95448E-01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .58162E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

SDT Tonnage Shipped by MSC to USAFE
GRAPH OF DIFFERENCE 1 ACF



PARTIAL AUTOCORRELATIONS

DATA - SDT Tonnage Shipped by MSC to USAFE 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .64980E+05
ST. DEV. OF SERIES = .17731E+05
NUMBER OF OBSERVATIONS = 40

1- 12	.85	.24	-.15	.07	.05	-.09	-.29	-.14	-.20	.21	.01	-.13
13- 24	-.05	-.01	-.09	.07	-.13	-.12	.08	-.03	.13	.05	-.17	.03

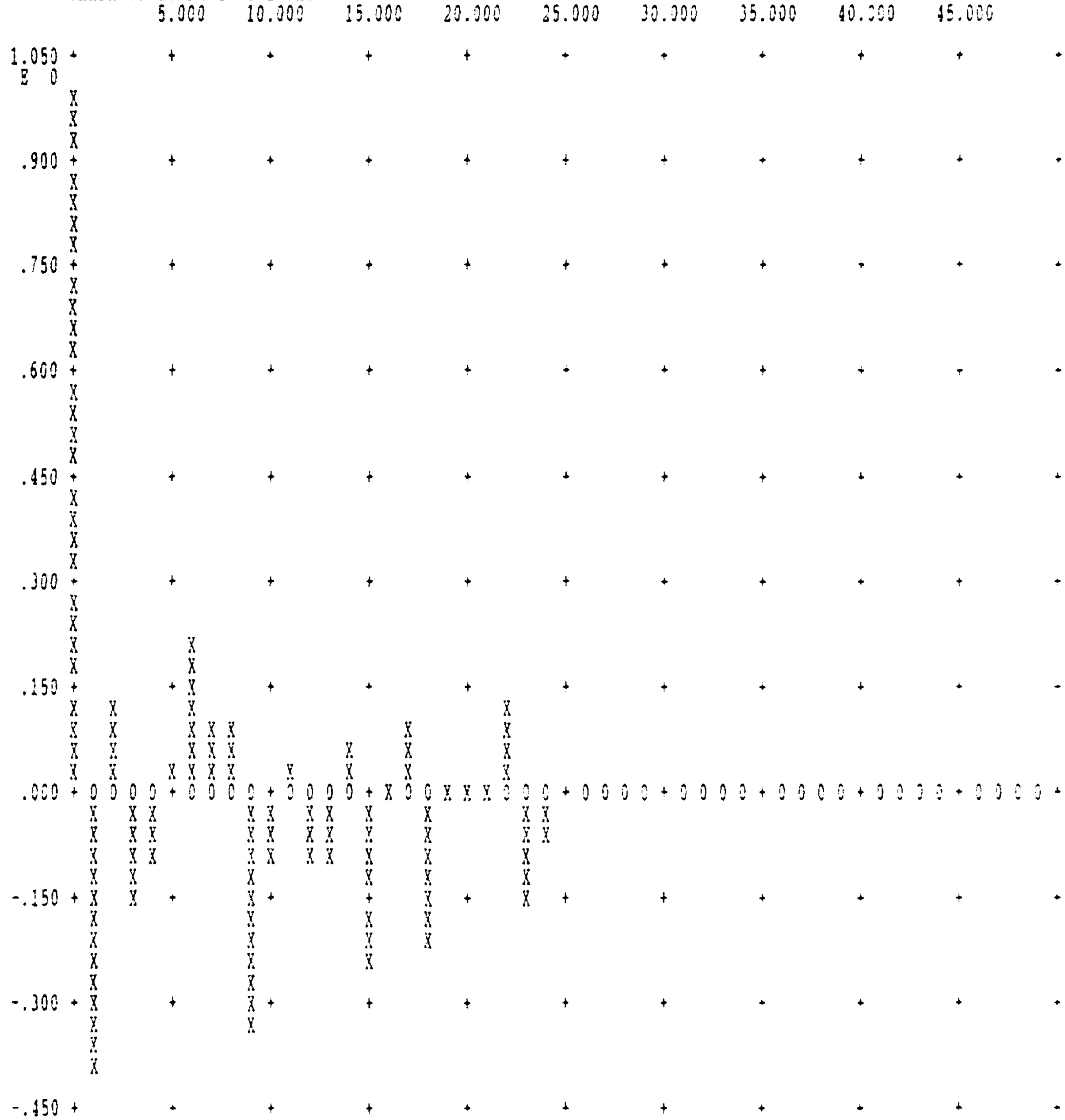
DIFFERENCE 1
MEAN OF THE SERIES = .58228E+03
ST. DEV. OF SERIES = .92546E+04
NUMBER OF OBSERVATIONS = 39

1- 12	-.38	.12	-.15	-.09	.04	.21	.09	.09	-.33	-.03	.02	-.09
13- 24	-.08	.05	-.24	.00	.08	-.20	-.01	.01	.01	.13	-.15	-.07

DIFFERENCE 2
MEAN OF THE SERIES = .24053E+03
ST. DEV. OF SERIES = .15534E+05
NUMBER OF OBSERVATIONS = 38

1- 12	-.72	-.24	-.24	-.27	-.33	-.12	-.09	.30	-.02	-.12	-.01	.00
13- 24	-.09	.14	-.15	-.16	.14	-.04	.02	.04	-.09	.15	.02	-.03

SDT Tonnage Shipped by MSC to USAFE
GRAPH OF DIFFERENCE 1 PACF



AUTOCORRELATION FUNCTION

DATA - SDT Tonnage Shipped by MAC to PACAF   40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .60774E+04
ST. DEV. OF SERIES = .42359E+03
NUMBER OF OBSERVATIONS = 40

1- 12	.33	-.05	-.07	-.01	-.09	-.03	-.04	-.17	-.13	-.19	-.14	.03
ST.E.	.16	.17	.18	.18	.18	.18	.18	.18	.18	.18	.19	.19
13- 24	.28	.12	.00	.02	-.05	-.16	.03	-.05	-.18	-.10	.02	.04
ST.E.	.19	.20	.20	.20	.20	.20	.21	.21	.21	.21	.21	.21

MEAN DIVIDED BY ST. ERROR = .90741E+02

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .15853E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

DIFFERENCE 1
MEAN OF THE SERIES = .11923E+02
ST. DEV. OF SERIES = .48217E+03
NUMBER OF OBSERVATIONS = 39

1- 12	-.18	-.29	-.08	.09	-.10	.05	.11	-.08	.09	-.06	-.14	-.11
ST.E.	.16	.17	.18	.18	.18	.18	.18	.18	.18	.19	.19	.19
13- 24	.34	.00	-.08	.04	-.01	-.21	.14	.06	-.07	-.06	.07	.06
ST.E.	.19	.20	.20	.21	.21	.21	.21	.21	.21	.21	.21	.22

MEAN DIVIDED BY ST. ERROR = .15443E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .15987E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

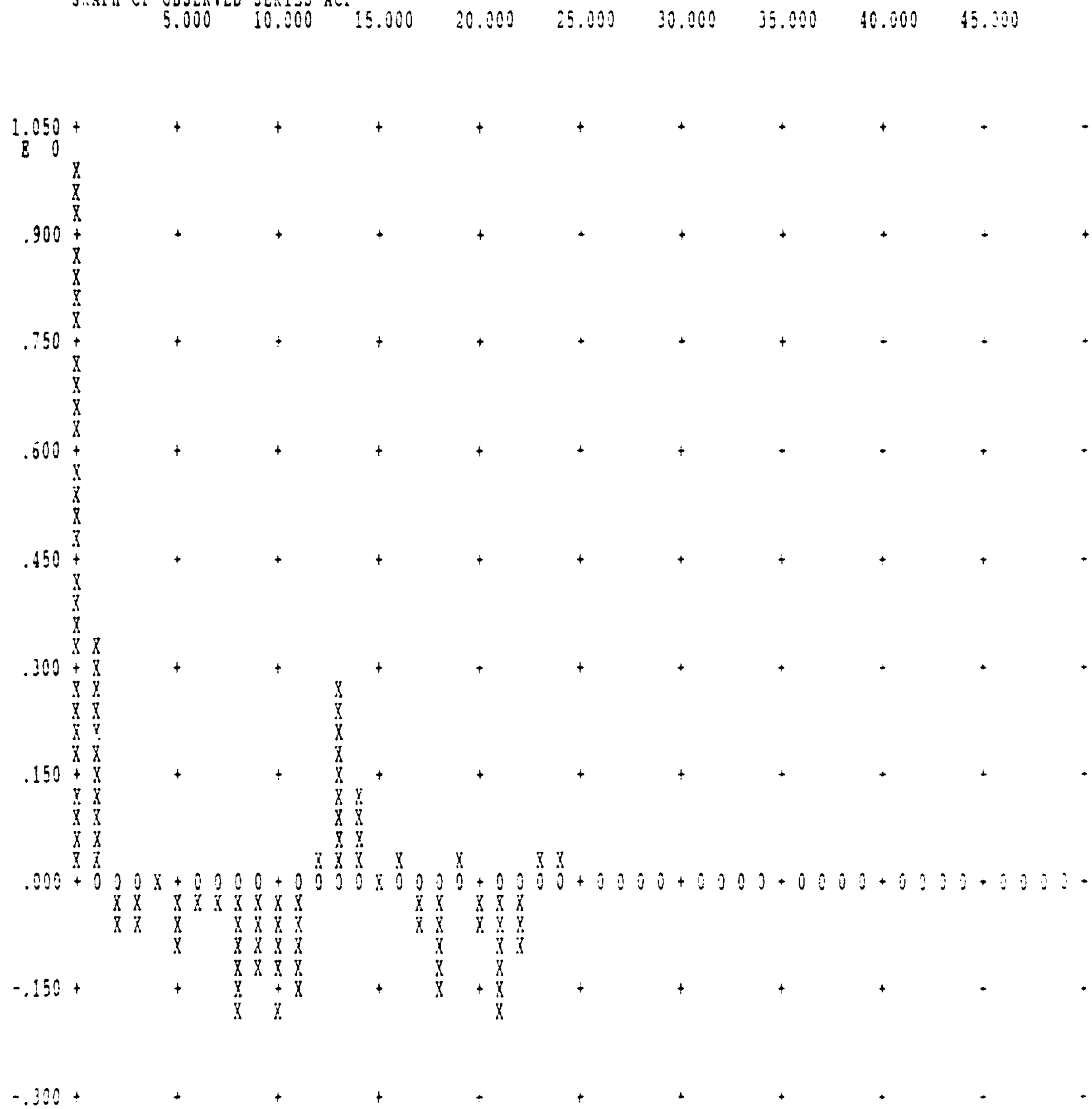
DIFFERENCE 2
MEAN OF THE SERIES = .27895E+02
ST. DEV. OF SERIES = .73900E+03
NUMBER OF OBSERVATIONS = 38

1- 12	-.42	-.14	.00	.15	-.09	-.01	.10	-.14	.12	.01	-.07	-.03
ST.E.	.16	.19	.19	.19	.19	.20	.20	.20	.20	.20	.20	.20
13- 24	.32	-.07	-.10	.07	.05	-.18	.14	-.02	-.02	-.08	.07	.06
ST.E.	.21	.22	.22	.22	.22	.22	.23	.23	.23	.23	.23	.23

MEAN DIVIDED BY ST. ERROR = .23263E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .19272E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

SDT Tonnage Shipped by MAC to PACAF
GRAPH OF OBSERVED SERISS ACF



PARTIAL AUTOCORRELATIONS

DATA - SDT Tonnage Shipped by MAC to PACAF 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .60774E+04
ST. DEV. OF SERIES = .42359E+03
NUMBER OF OBSERVATIONS = 40

1- 12	.33	-.18	.02	.00	-.11	.05	-.08	-.16	-.01	-.22	-.04	.05
13- 24	.21	-.07	.00	.00	-.13	-.14	.10	-.22	-.06	.00	.07	.08

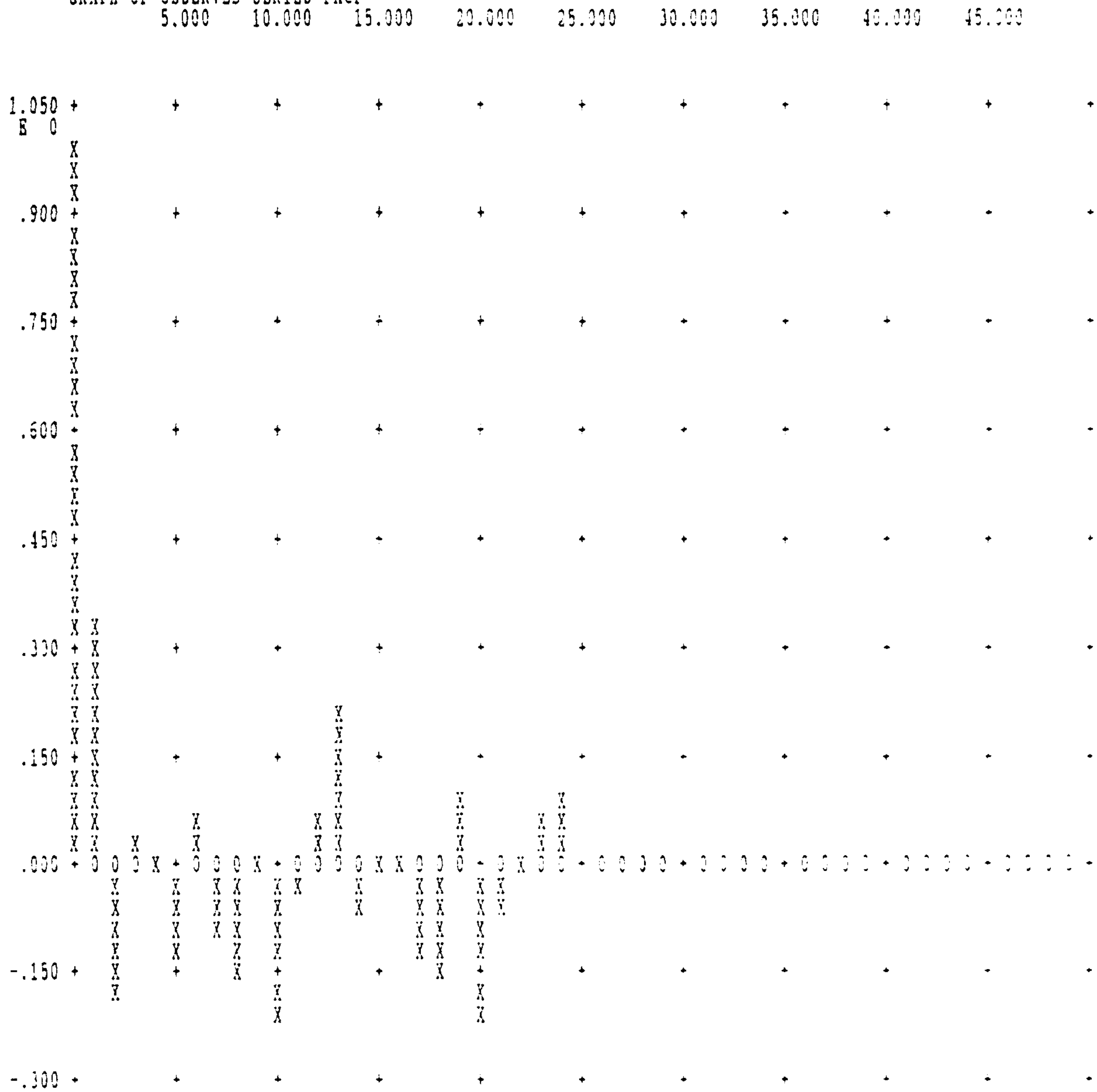
DIFFERENCE 1
MEAN OF THE SERIES = .11923E+02
ST. DEV. OF SERIES = .48217E+03
NUMBER OF OBSERVATIONS = 39

1- 12	-.18	-.33	-.24	-.11	-.05	-.10	-.01	-.11	.12	-.03	-.14	-.23
13- 24	.12	.00	.07	.14	.09	-.11	.12	-.04	-.04	-.18	-.10	.06

DIFFERENCE 2
MEAN OF THE SERIES = .27895E+02
ST. DEV. OF SERIES = .73900E+03
NUMBER OF OBSERVATIONS = 38

1- 12	-.42	-.39	-.36	-.16	-.19	-.17	.08	-.15	.03	.12	.07	-.25
13- 24	.00	-.03	-.05	.08	.13	-.09	.10	-.04	.05	-.12	-.23	-.12

SDT Tonnage Shipped by MAC to PACAF
GRAPH OF OBSERVED SERIES PACF



AUTOCORRELATION FUNCTION

DATA - SDT Tonnage Shipped by MSC to PACAF 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .39198E+05
ST. DEV. OF SERIES = .70790E+04
NUMBER OF OBSERVATIONS = 40

1- 12	.77	.66	.54	.49	.34	.26	.18	.19	.13	.17	.11	[illegible]
ST.E.	.16	.23	.28	.30	.32	.33	.33	.34	.34	.34	.34	.35
13- 24	-.08	-.14	-.19	-.30	-.39	-.35	-.34	-.31	-.35	-.26	-.24	-.25
ST.E.	.35	.35	.35	.35	.36	.37	.37	.38	.39	.40	.40	.40

MEAN DIVIDED BY ST. ERROR = .35020E+02

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .11348E+03
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

DIFFERENCE 1
MEAN OF THE SERIES = .14200E+03
ST. DEV. OF SERIES = .47073E+04
NUMBER OF OBSERVATIONS = 39

1- 12	-.30	.06	-.17	.03	-.16	.01	-.17	.01	.02	.14	[illegible]	[illegible]
ST.E.	.16	.17	.17	.18	.19	.19	.19	.19	.19	.19	[illegible]	[illegible]
13- 24	-.17	-.01	.15	-.30	-.01	[illegible]	-.03	.17	-.25	.16	[illegible]	[illegible]
ST.E.	.20	[illegible]	[illegible]	.20	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

MEAN DIVIDED BY ST. ERROR = .18833E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .19987E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

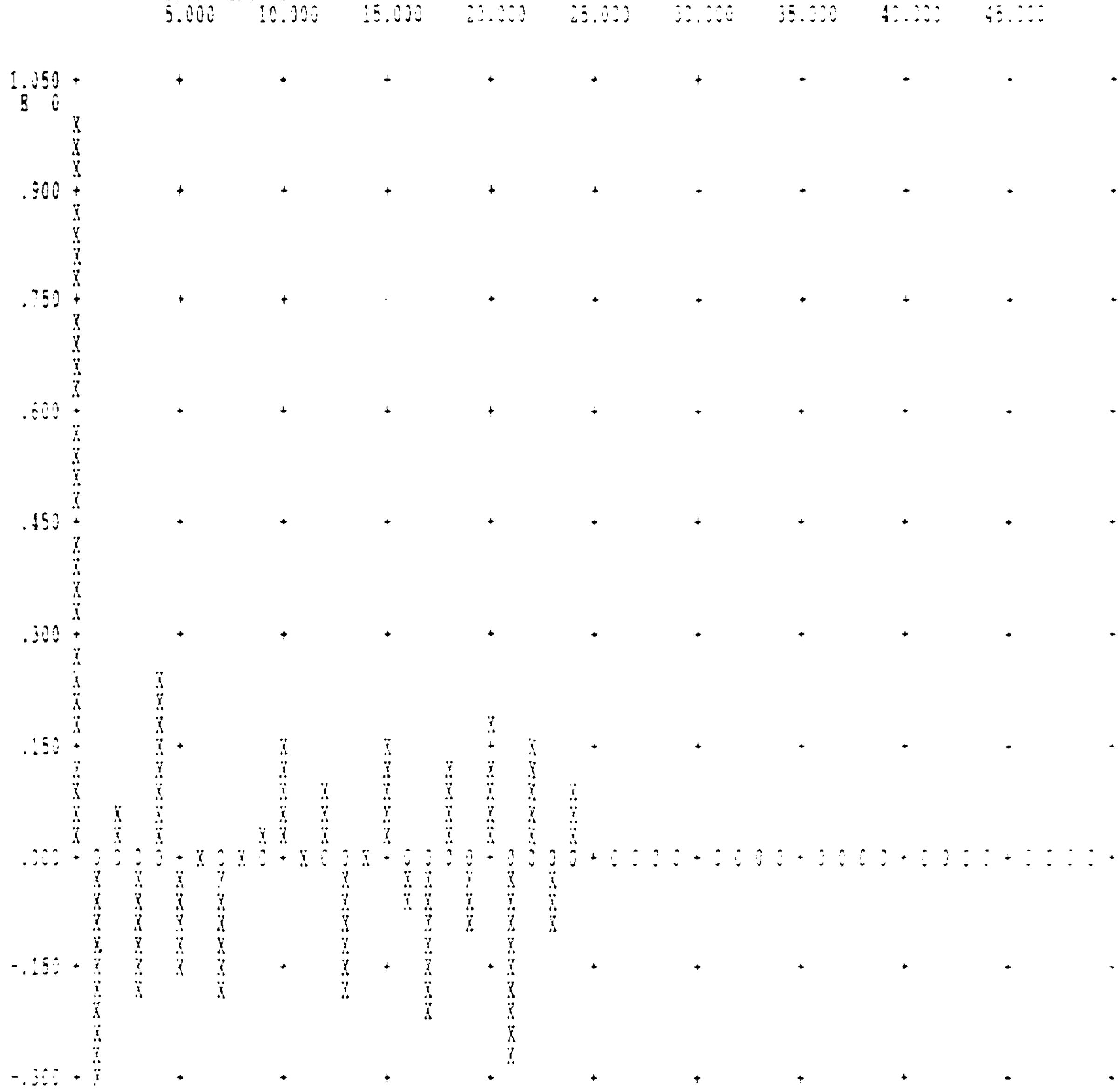
DIFFERENCE 2
MEAN OF THE SERIES = .71368E+02
ST. DEV. OF SERIES = .76938E+04
NUMBER OF OBSERVATIONS = 38

1- 12	-.63	[illegible]	-.25	[illegible]	[illegible]	.14	-.15	[illegible]	-.07	[illegible]	[illegible]	[illegible]
ST.E.	.16	.22	.22	.22	.24	.25	.25	.25	.25	.25	.25	.25
13- 24	-.16	.30	.15	-.21	-.19	.13	-.16	.26	-.31	.25	-.15	[illegible]
ST.E.	.26	.26	.26	.26	.26	.26	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

MEAN DIVIDED BY ST. ERROR = .57139E-01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .44436E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 24 DEGREES OF FREEDOM

SDT Tonnage Shipped by MSC to PACAF
GRAPH OF DIFFERENCE 1 ACF



PARTIAL AUTOCORRELATIONS

DATA - SDT Tonnage Shipped by MSC to PACAF 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES = .39193E+05
ST. DEV. OF SERIES = .70790E+04
NUMBER OF OBSERVATIONS = 40

1- 12	.77	.17	-.02	.11	-.22	-.03	.00	.14	.11	-.02	[illegible]	-.04
13- 24	-.02	.00	.11	-.15	-.12	.11	-.13	.07	-.11	.04	[illegible]	-.09

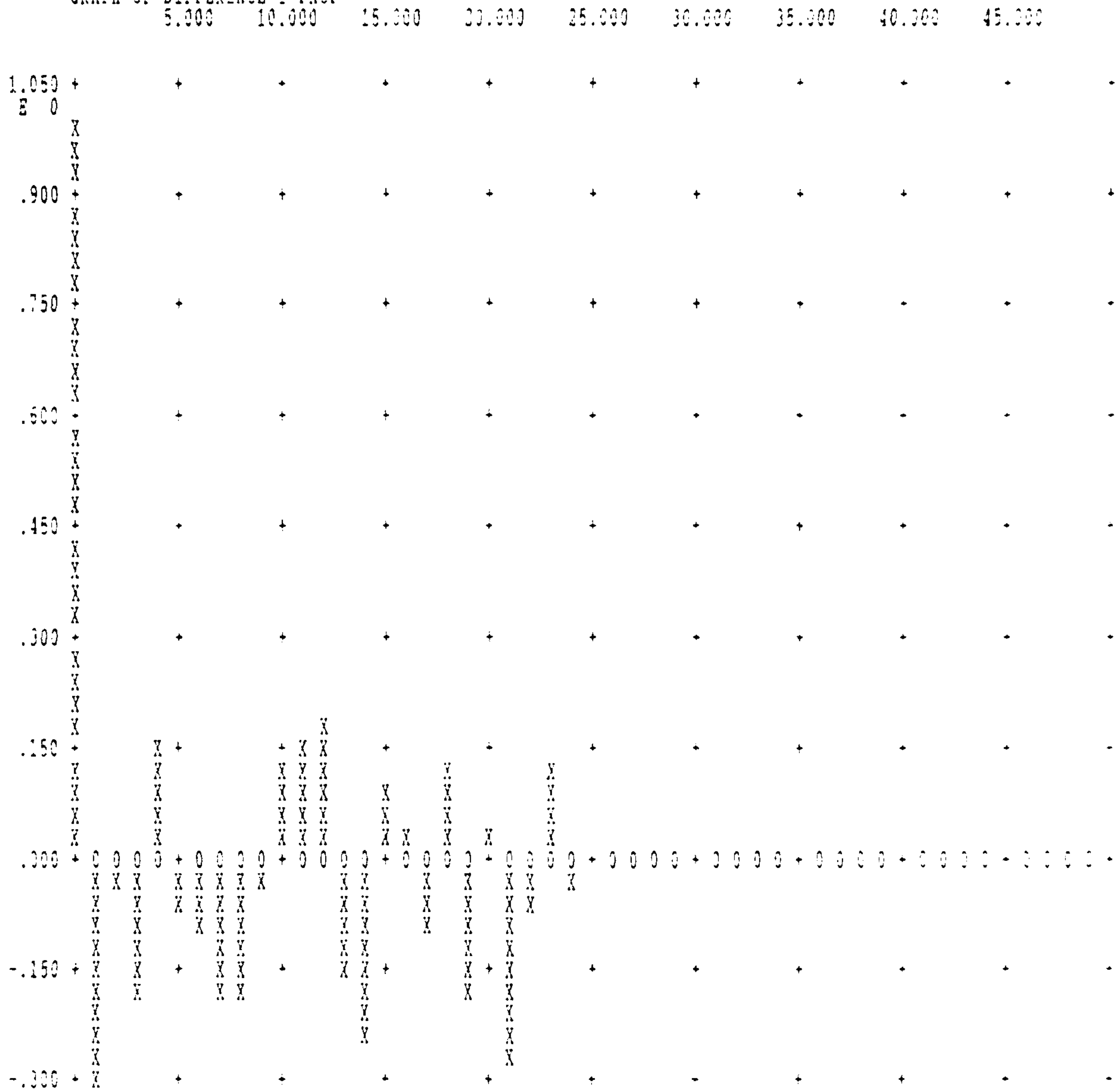
DIFFERENCE 1
MEAN OF THE SERIES = .14200E+03
ST. DEV. OF SERIES = .47073E+04
NUMBER OF OBSERVATIONS = 39

1- 12	-.30	-.04	-.18	.15	-.06	-.08	-.17	-.17	-.02	.12	.15	.17
13- 24	-.16	-.23	.09	.03	-.10	.13	-.17	.02	-.13	-.06	.11	-.04

DIFFERENCE 2
MEAN OF THE SERIES = .71368E+02
ST. DEV. OF SERIES = .76923E+04
NUMBER OF OBSERVATIONS = 38

1- 12	-.63	-.29	-.46	-.14	-.11	-.01	-.04	-.16	-.14	-.11	-.16	.14
13- 24	.14	-.20	-.03	.06	-.15	.12	-.01	.16	-.10	-.00	-.01	-.07

SDT Tonnage Shipped by MSC to PACAF
GRAPH OF DIFFERENCE 1 PACF



Appendix D: TIMES Forecasting Computer Output

SUMMARY OF SDT Tonnage Shipped by MAC to USAFE

****

DATA - Z = SDT Tonnage Shipped by MAC to USAFE 40 OBSERVATIONS

DIFFERENCING ON Z - 2 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	2	-.50572E+00	-.81446E+00	-.19697E+00
2	MOVING AVERAGE 1	1	.14292E+01	.11456E+01	.17128E+01
3	MOVING AVERAGE 1	2	-.73174E+00	-.10329E+01	-.44055E+00

****

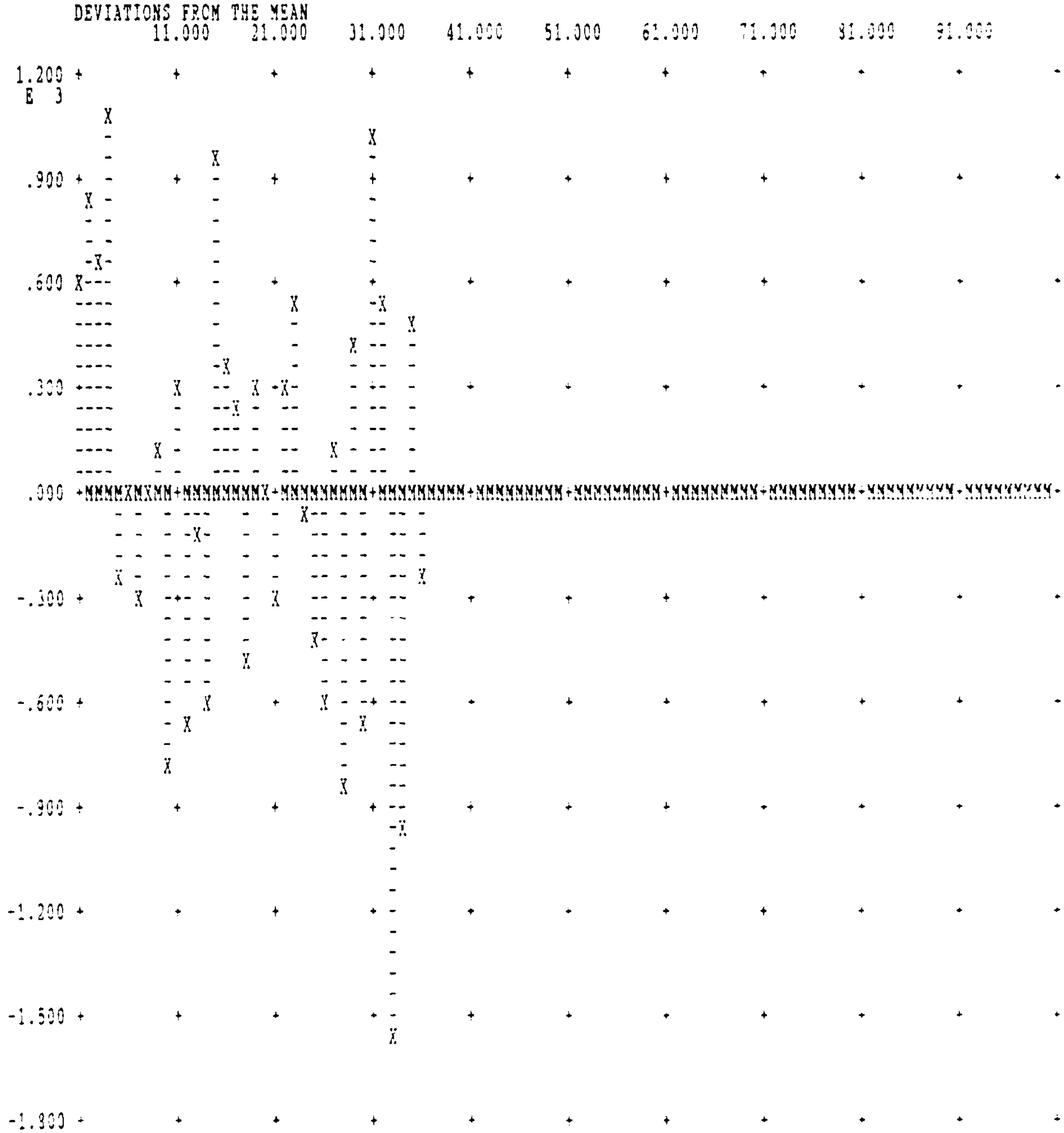
OTHER INFORMATION AND RESULTS

****

RESIDUAL SUM OF SQUARES .13133E+08 33 D.F. RESIDUAL MEAN SQUARE .39793E+06

NUMBER OF RESIDUALS 36 RESIDUAL STANDARD ERROR .63085E+03

THE ESTIMATED RESIDUALS -- MODEL 1
OBSERVED SERIES
DEVIATIONS FROM THE MEAN



AUTOCORRELATION FUNCTION

DATA - THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to USAFE 36 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

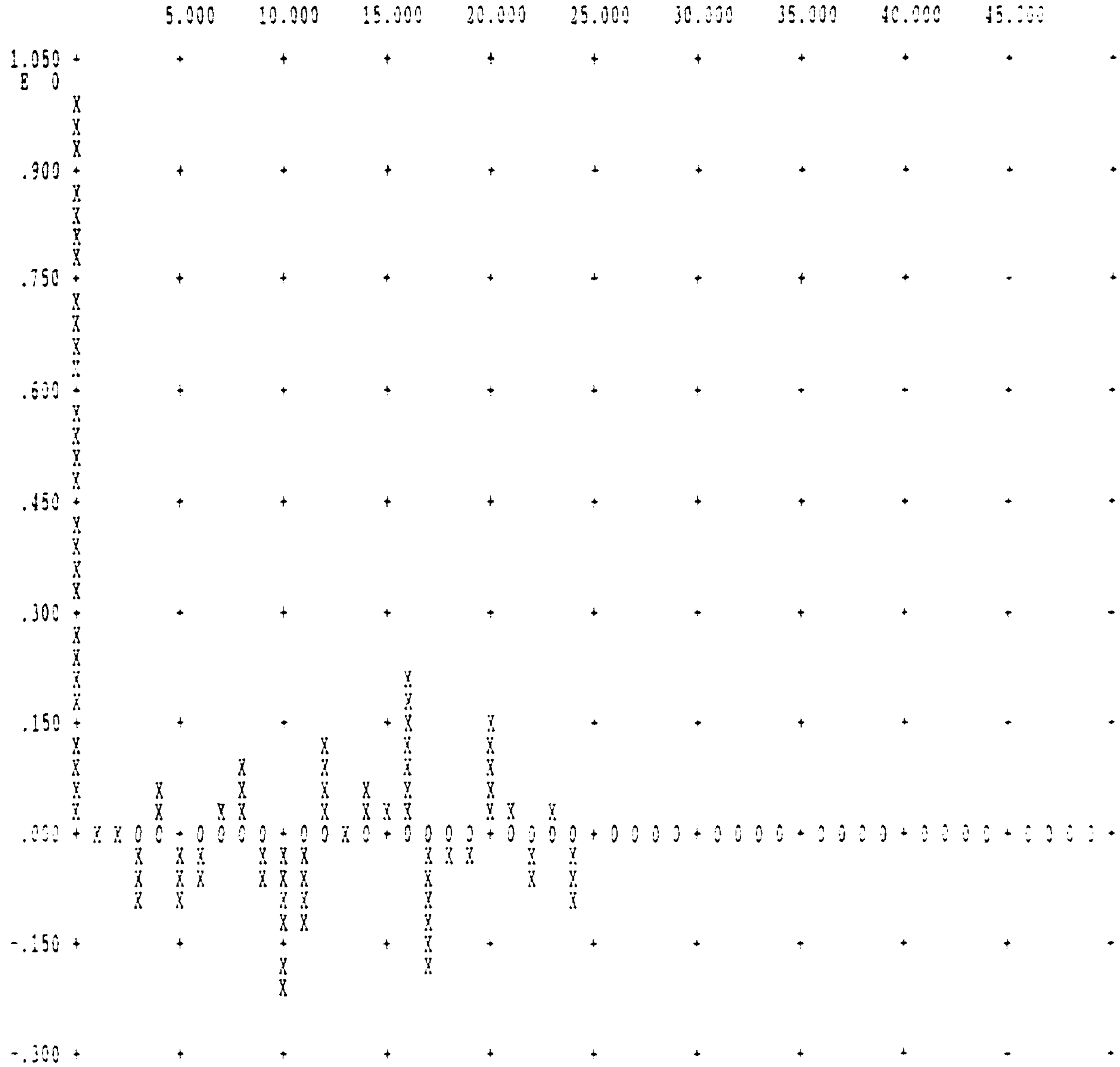
ORIGINAL SERIES
MEAN OF THE SERIES = .47858E+02
ST. DEV. OF SERIES = .61064E+03
NUMBER OF OBSERVATIONS = 36

1- 12	.01	.00	-.09	.06	-.09	-.05	.04	.09	-.06	-.20	[illegible]	[illegible]
ST.E.	.17	.17	.17	.17	.17	.17	.17	.17	.17	.17	.18	.18
13- 24	.00	.07	.04	.20	-.17	-.03	-.04	.15	.03	-.06	.04	-.09
ST.E.	.18	.18	.19	.19	.19	.20	.20	.20	.20	.20	[illegible]	[illegible]

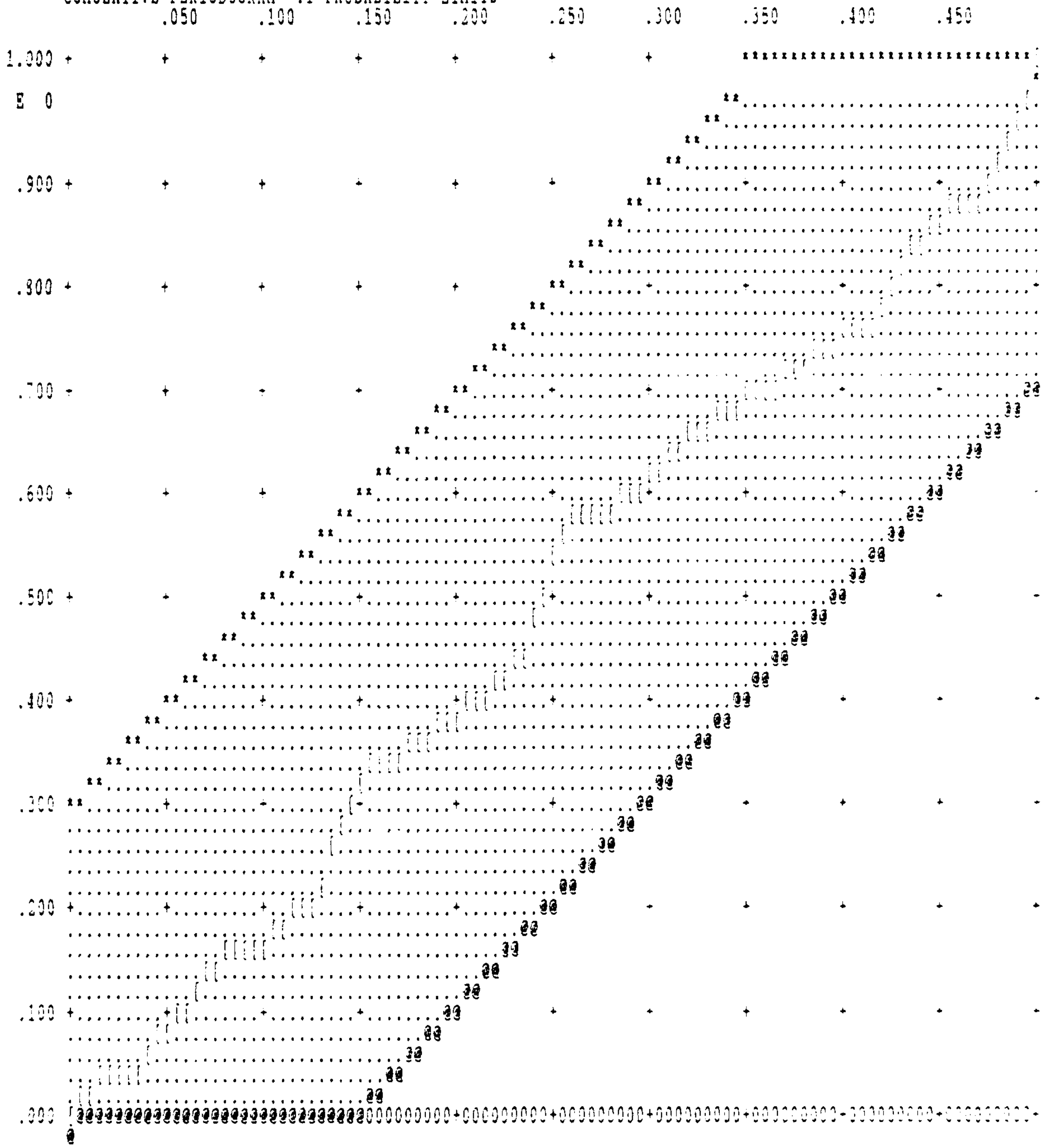
MEAN DIVIDED BY ST. ERROR = .47024E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .82759E+01
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 21 DEGREES OF FREEDOM

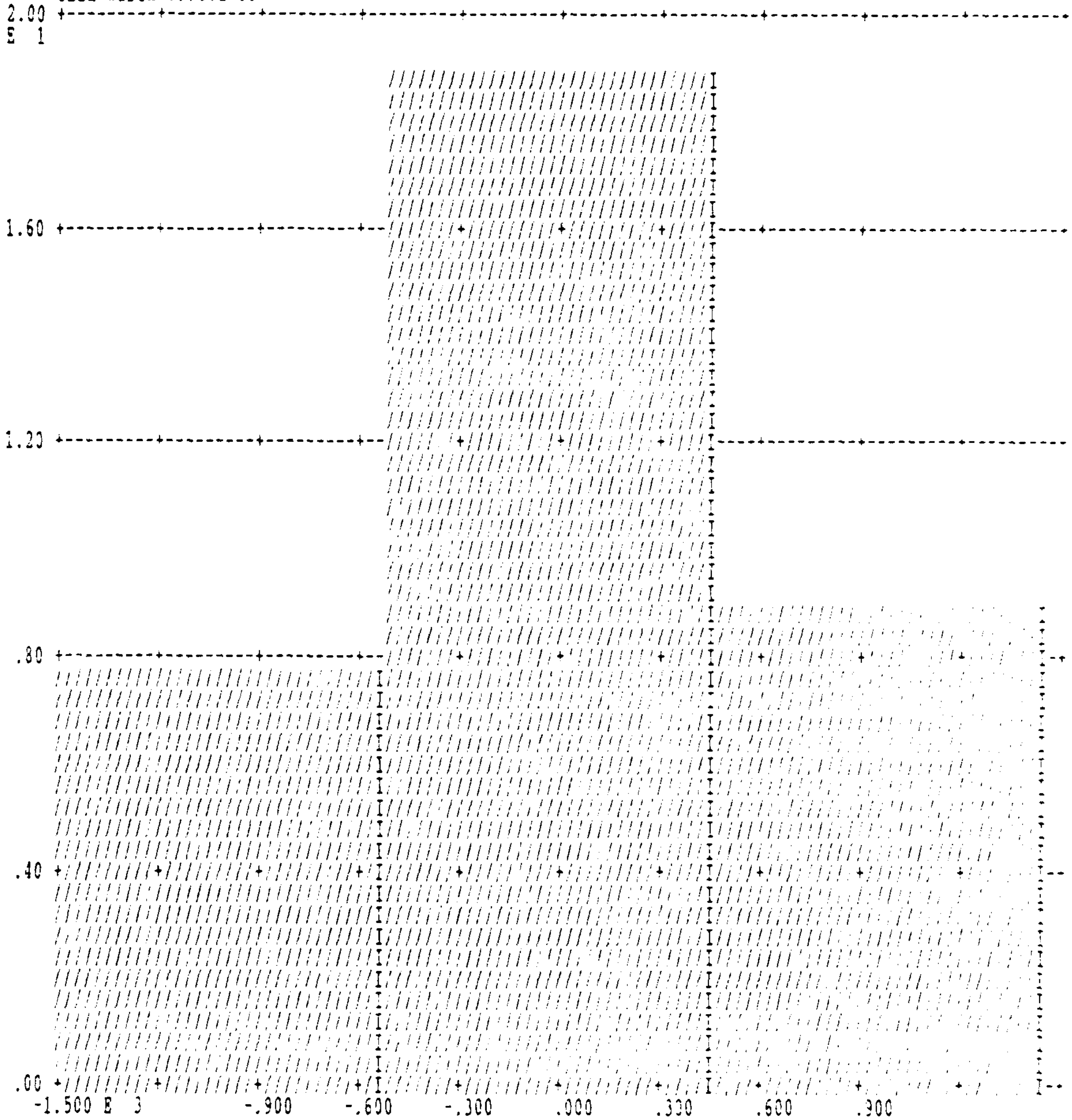
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to USAFE
GRAPH OF OBSERVED SERIES ACF



THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to USAFE
CUMULATIVE PERIODOGRAM .1 PROBABILITY LIMITS



THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to USAFE
HISTOGRAM
CELL WIDTH .9900E+03



PREWHITENED SDT Tonnage Shipped by MAC to USAFE
LOG10 SPECTRUM   SMOOTHING BANDWIDTH = .098   APPROX 95 P.C. CONFIDENCE LIMITS

.050 .100 .150 .200 .250 .300 .350 .400 .450

TIME SERIES FORECASTING FOR SDT Tonnage Shipped by MAC to USAFE

****

DATA - Z = SDT Tonnage Shipped by MAC to USAFE 40 OBSERVATIONS

DIFFERENCING ON Z - 2 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE
1	AUTOREGRESSIVE 1	2	-.50572E+00
2	MOVING AVERAGE 1	1	.14292E+01
3	MOVING AVERAGE 1	2	-.73174E+00

****

NUMBER OF TIME ORIGINS FOR FORECASTS = 1

NUMBER OF FORECASTS AT EACH TIME ORIGIN = 6

FORECAST TIME ORIGINS ARE T = 40

SDT Tonnage Shipped by MAC to USAFE FORECASTS BASE PERIOD 40 WITH 95 PER CENT CONFIDENCE LIMITS

PERIODS AHEAD	LO. CONF. LIMIT	FORECAST	UP. CONF. LIMIT
1	.7279630E+04	.8516104E+04	.9752579E+04
2	.7207063E+04	.8630789E+04	.1005451E+05
3	.7395529E+04	.8890057E+04	.1038458E+05
4	.6688235E+04	.8542168E+04	.1039610E+05
5	.5673476E+04	.8121161E+04	.1056884E+05
6	.5056806E+04	.8007205E+04	.1095760E+05

SUMMARY OF SDT Tonnage Shipped by MSC to USAFE

****

DATA - Z = SDT Tonnage Shipped by MSC to USAFE 40 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.80900E+00	-.11324E+01	-.43561E+00
2	MOVING AVERAGE 1	1	-.57530E+00	-.11220E+01	-.28626E-01

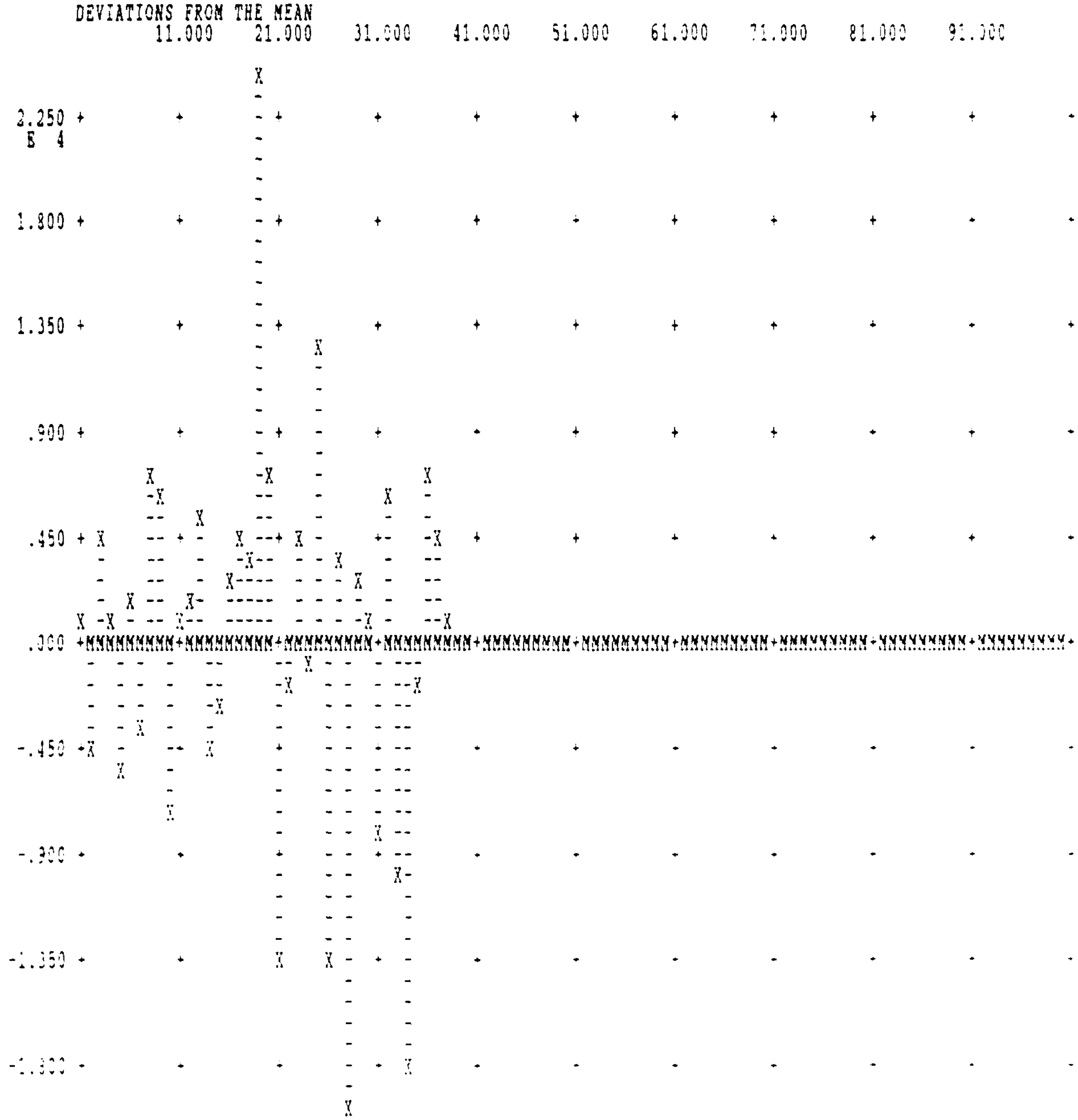
****

OTHER INFORMATION AND RESULTS

****

RESIDUAL SUM OF SQUARES	.25915E+10	36 D.F.	RESIDUAL MEAN SQUARE	.71987E+08
NUMBER OF RESIDUALS	38		RESIDUAL STANDARD ERROR	.84845E+04

THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to USAFE
OBSERVED SERIES
DEVIATIONS FROM THE MEAN



AUTOCORRELATION FUNCTION

DATA - THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to USAFE 38 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

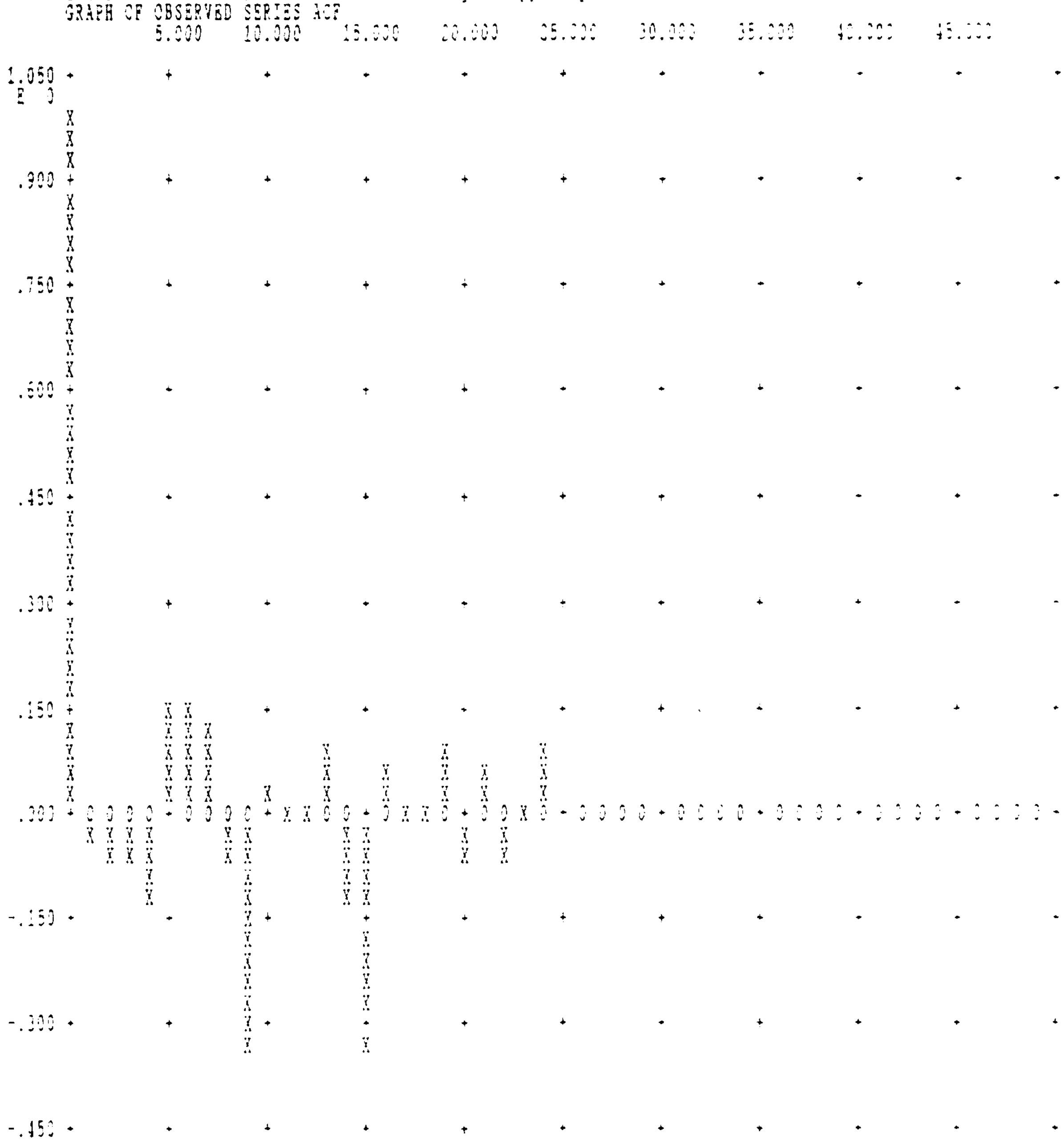
ORIGINAL SERIES
MEAN OF THE SERIES = .83431E+03
ST. DEV. OF SERIES = .83262E+04
NUMBER OF OBSERVATIONS = 38

1- 12	-.04	-.06	-.07	-.12	.15	.14	.12	-.06	-.04	.02	[illegible]	[illegible]
ST.E.	.16	.16	.16	.16	.17	.17	.17	.18	.18	.19	.19	.19
13- 24	.09	-.11	-.10	.07	.01	-.01	.08	-.06	.05	-.07	.01	.09
ST.E.	.19	.19	.19	.21	.21	.21	.21	.21	.21	.21	.21	.21

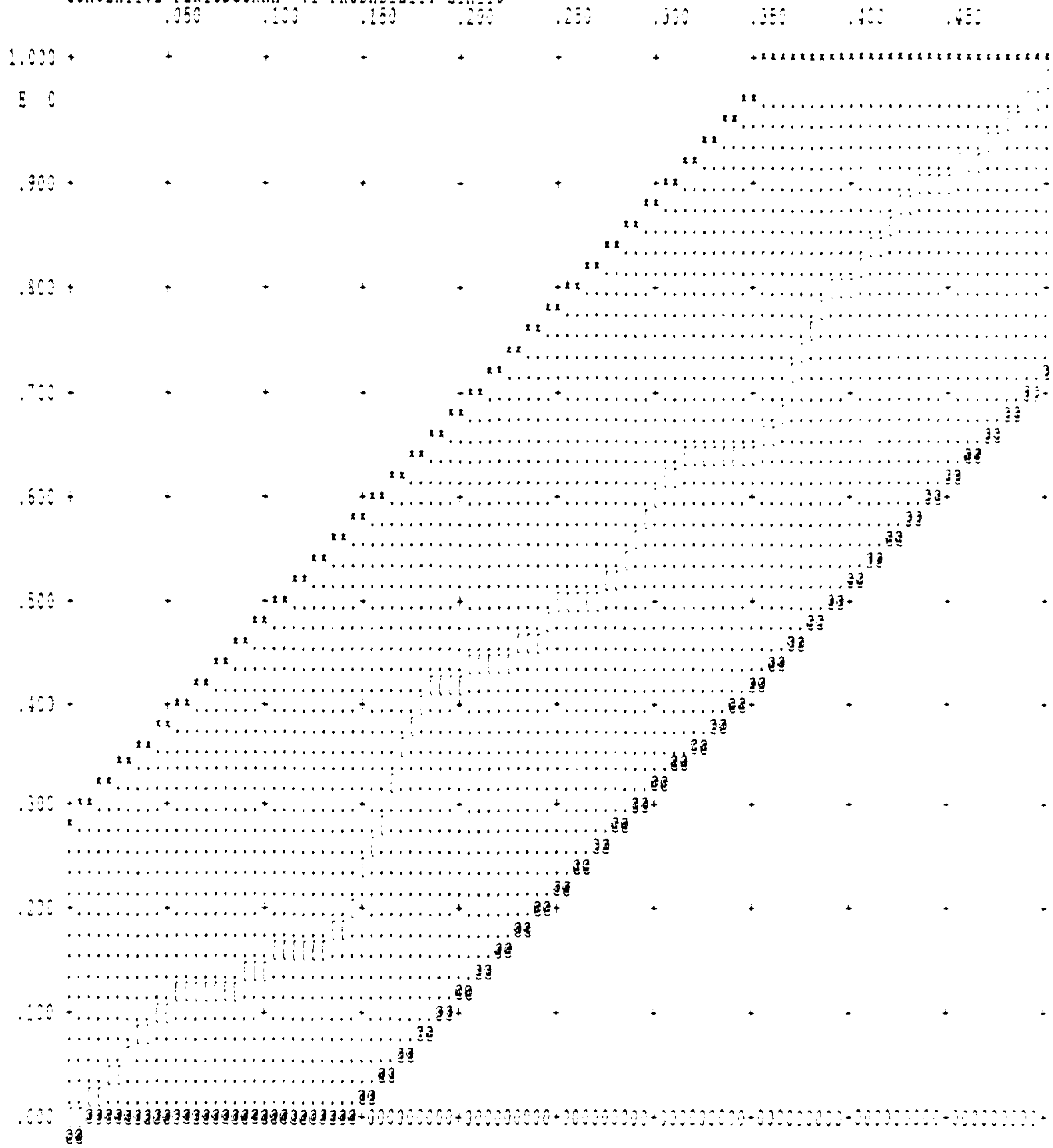
MEAN DIVIDED BY ST. ERROR = .61769E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .10505E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 22 DEGREES OF FREEDOM

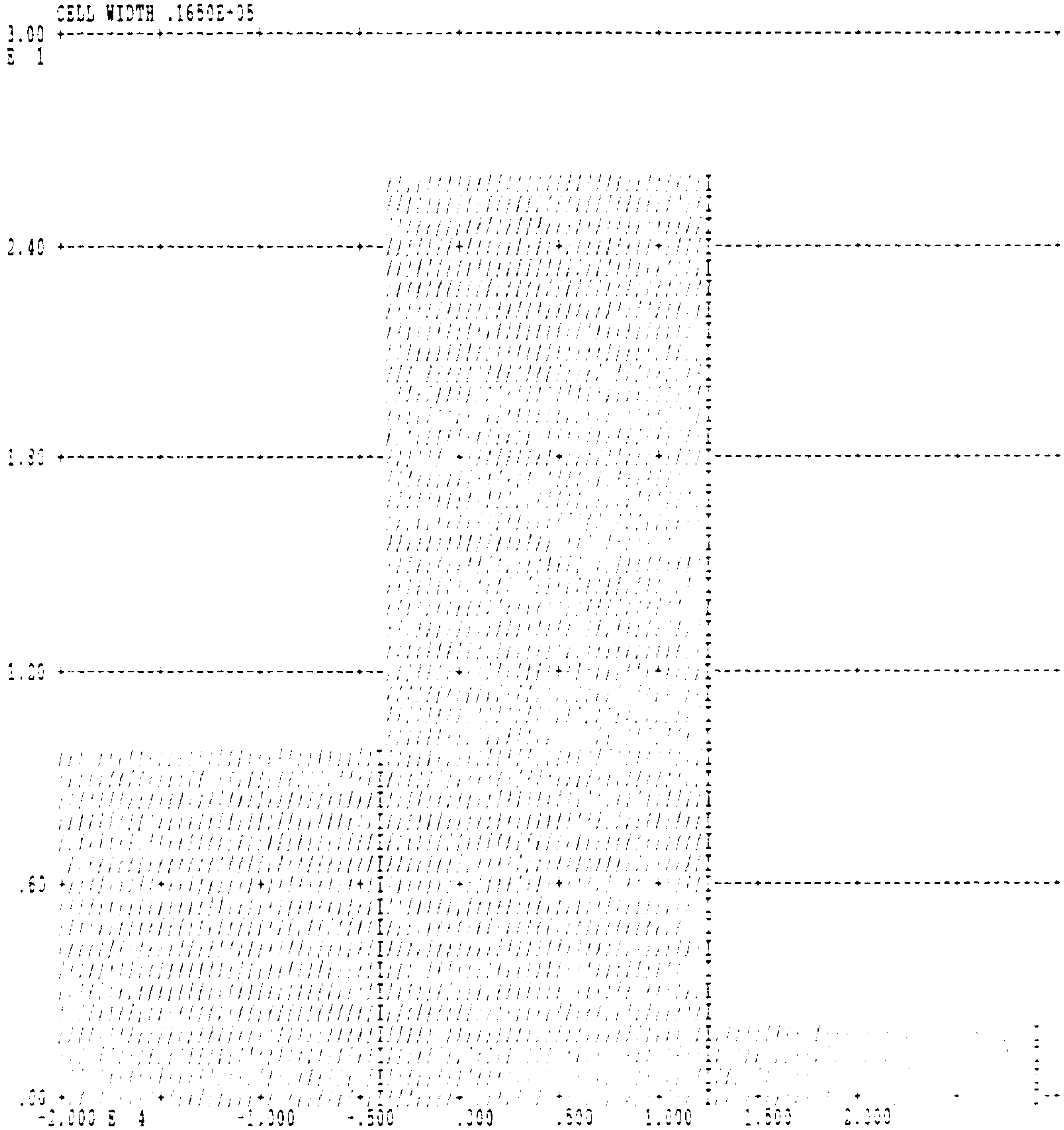
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to USAFE
GRAPH OF OBSERVED SERIES ACF



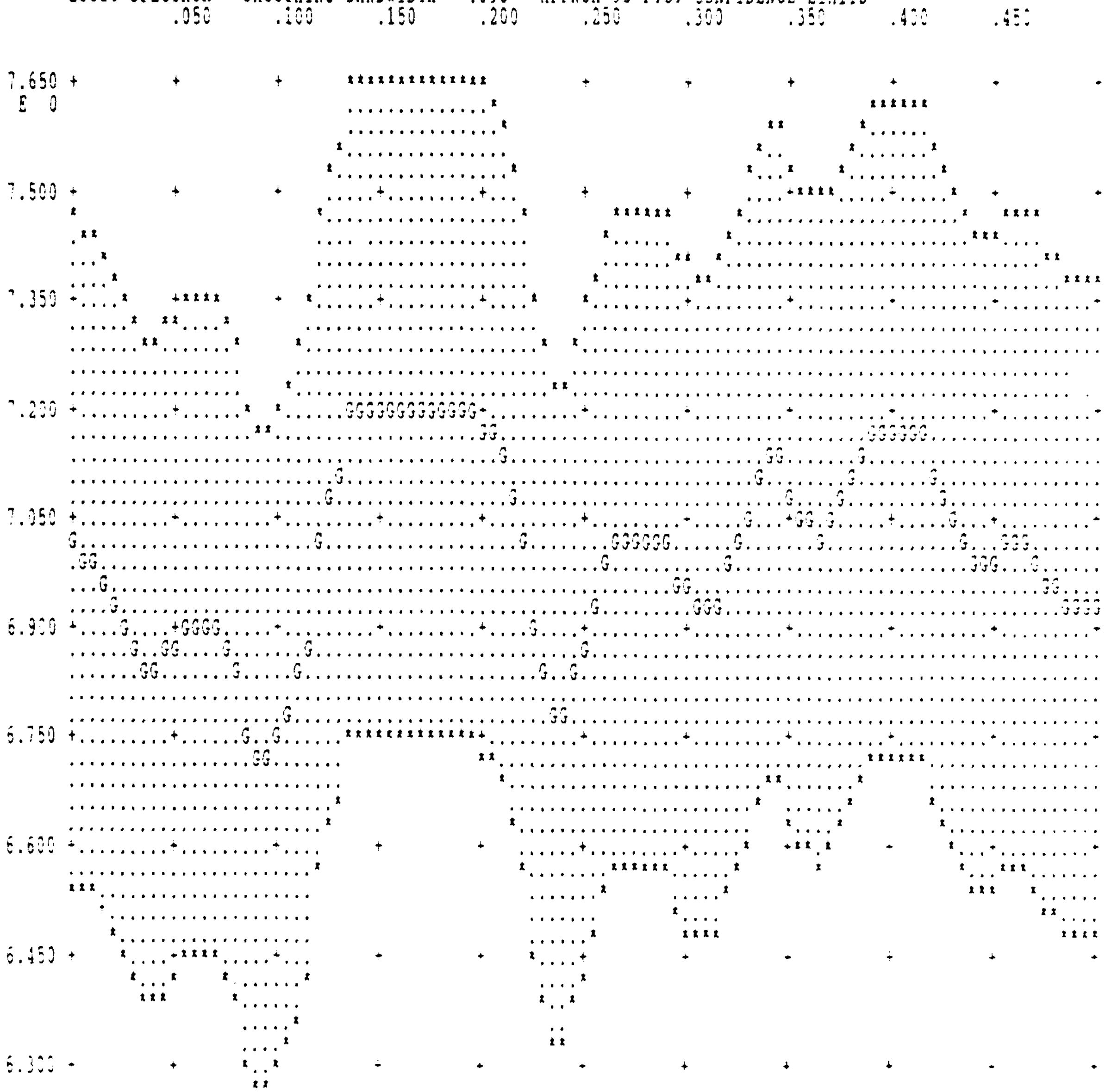
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to USAFE
CUMULATIVE PERIODOGRAM .1 PROBABILITY LIMITS



THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to USAFE
HISTOGRAM
CELL WIDTH .1650E+05



PREWHITENED SDT Tonnage Shipped by MSC to USAFE
LOG10 SPECTRUM   SMOOTHING BANDWIDTH = .098   APPROX 95 P.C. CONFIDENCE LIMITS



TIME SERIES FORECASTING FOR SDT Tonnage Shipped by MSC to USAFE

****

DATA - Z = SDT Tonnage Shipped by MSC to USAFE 40 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE
1	AUTOREGRESSIVE 1	1	-.30900E+00
2	MOVING AVERAGE 1	1	-.57530E+00

****

NUMBER OF TIME ORIGINS FOR FORECASTS = 1

NUMBER OF FORECASTS AT EACH TIME ORIGIN = 6

FORECAST TIME ORIGINS ARE T = 40

SDT Tonnage Shipped by MSC to USAFE FORECASTS BASE PERIOD 40 WITH 95 PER CENT CONFIDENCE LIMITS

PERIODS AHEAD	LO. CONF. LIMIT	FORECAST	UP. CONF. LIMIT
1	.5339166E+05	.7002123E+05	.8665091E+05
2	.4863826E+05	.6958905E+05	.9053984E+05
3	.4364533E+05	.6993873E+05	.9623213E+05
4	.4017025E+05	.6965584E+05	.9914142E+05
5	.3661900E+05	.6998470E+05	.1033504E+06
6	.3370918E+05	.6969955E+05	.1056899E+06

SUMMARY OF SDT Tonnage Shipped by MAC to PACAF

****

DATA - Z = SDT Tonnage Shipped by MAC to PACAF 40 OBSERVATIONS

DIFFERENCING ON Z - NONE

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	UPPER LIMIT
1	MEAN	0	.60644E+04	.58891E+04	.62396E+04
2	MOVING AVERAGE 1	1	-.40823E+00	-.71354E+00	-.10291E+00

****

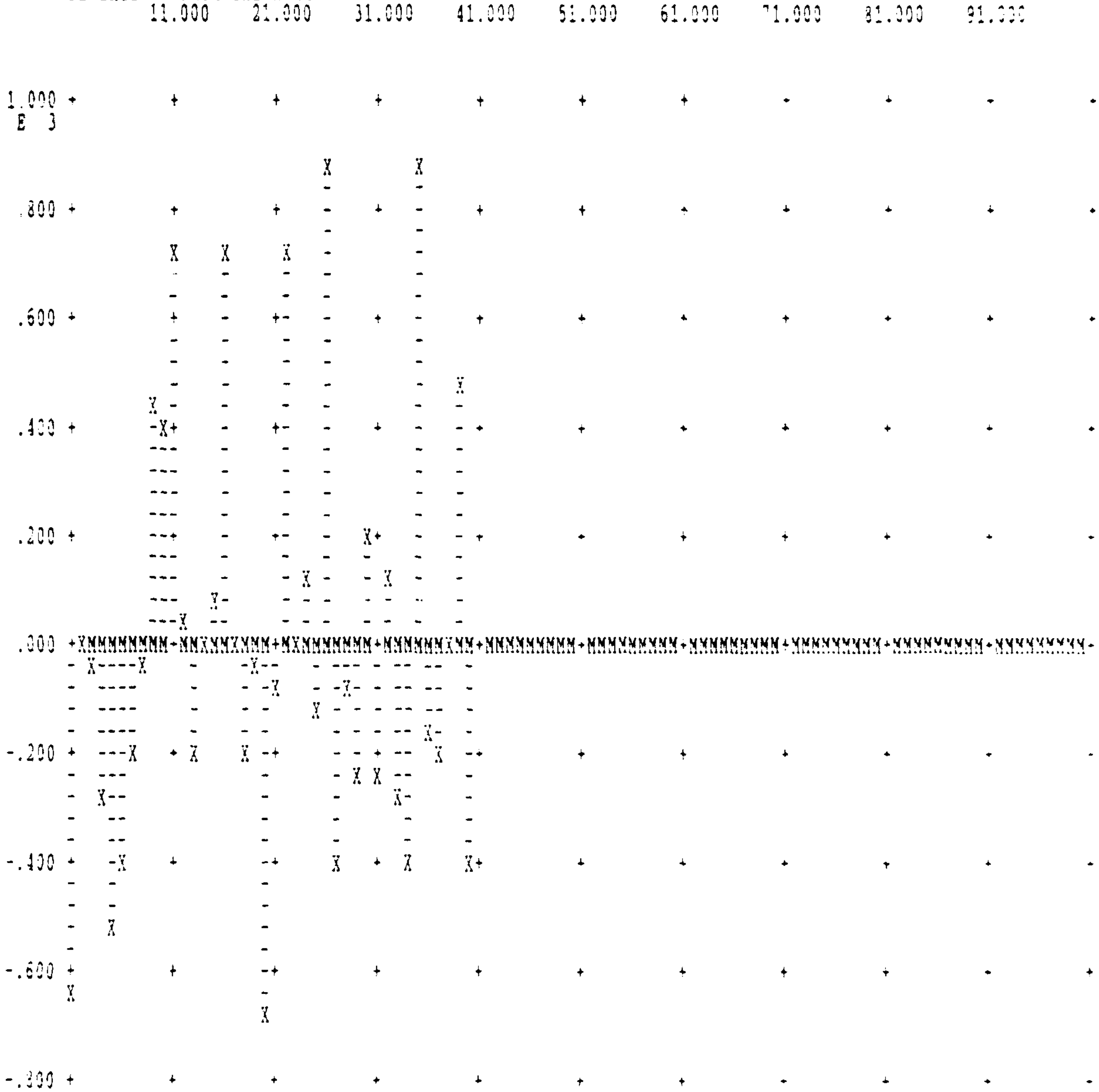
OTHER INFORMATION AND RESULTS

****

RESIDUAL SUM OF SQUARES .60113E+07 38 D.F. RESIDUAL MEAN SQUARE .15819E+06

NUMBER OF RESIDUALS 40 RESIDUAL STANDARD ERROR .39773E+03

THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to USAFE
OBSERVED SERIES
DEVIATIONS FROM THE MEAN



AUTOCORRELATION FUNCTION

DATA - THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to PACAF 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

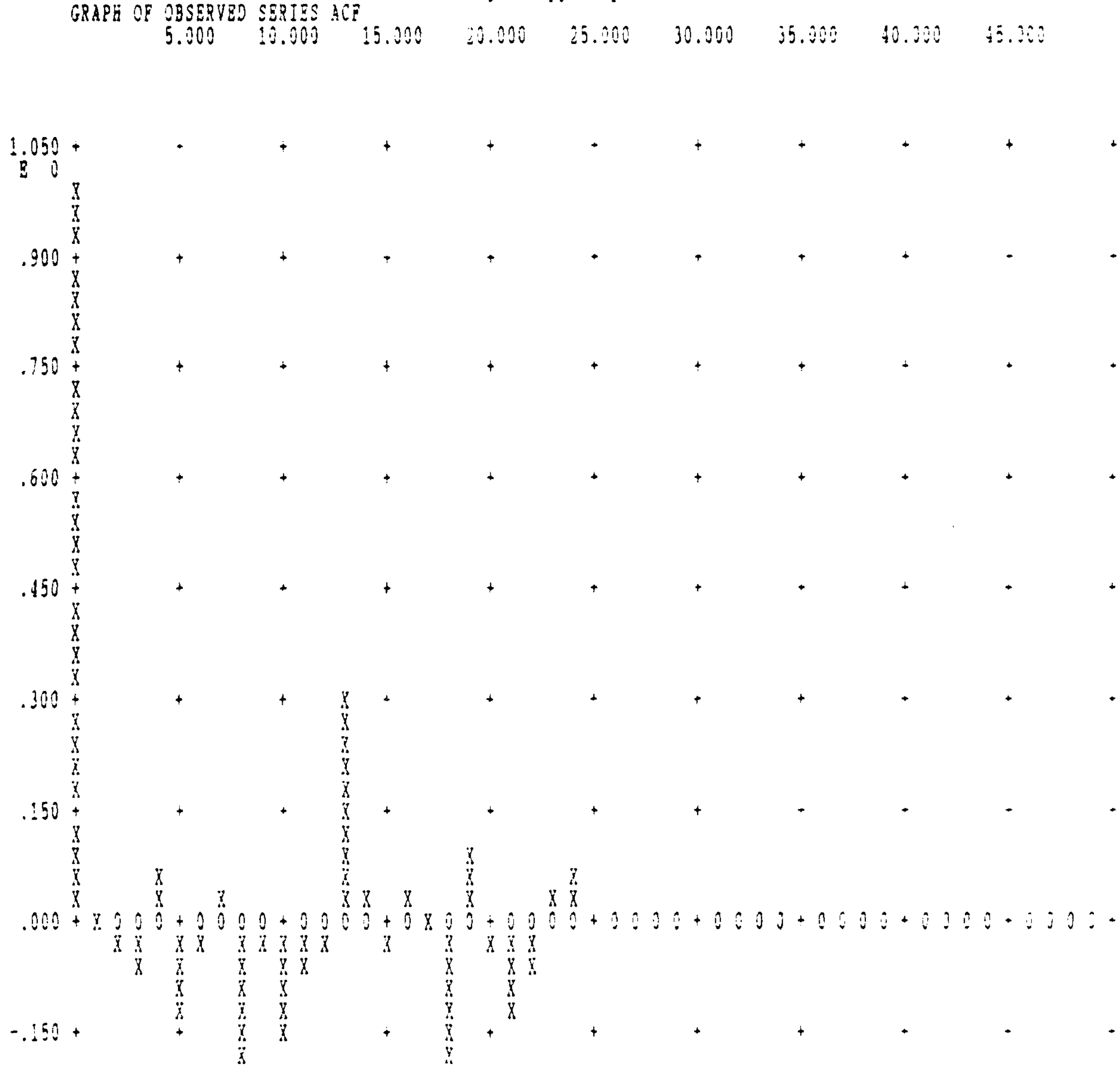
ORIGINAL SERIES
MEAN OF THE SERIES = .65003E+01
ST. DEV. OF SERIES = .39255E+03
NUMBER OF OBSERVATIONS = 40

1- 12	.00	-.04	-.07	.05	-.11	-.02	.03	-.17	-.02	-.15	-.07	-.04
ST.E.	.16	.16	.16	.16	.16	.16	.16	.16	.17	.17	.17	.17
13- 24	.29	.04	-.04	.03	.00	-.19	.08	-.02	-.13	-.06	.03	.06
ST.E.	.17	.18	.18	.18	.18	.18	.19	.19	.19	.19	.19	.19

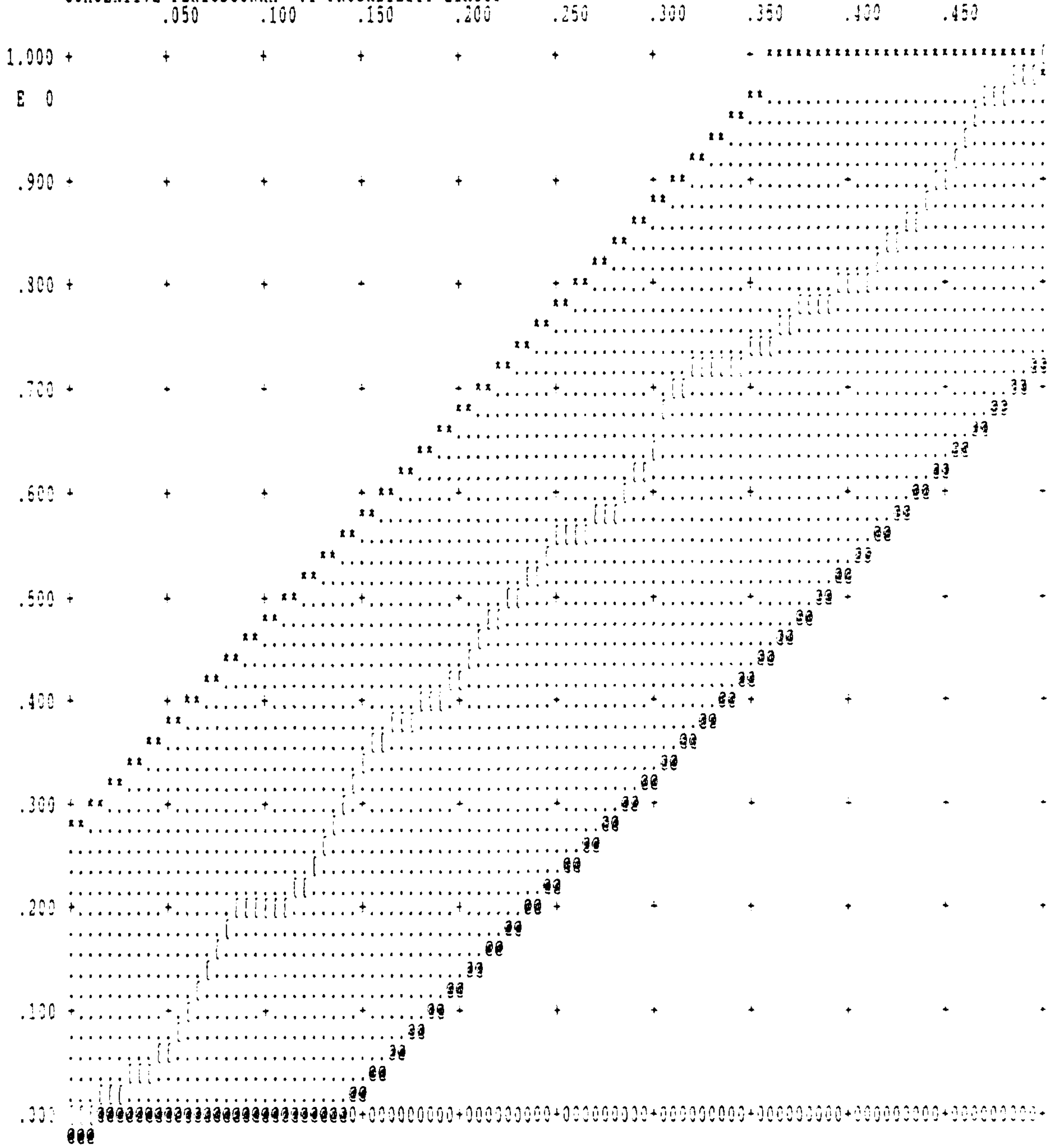
MEAN DIVIDED BY ST. ERROR = .10473E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .94246E+01
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 22 DEGREES OF FREEDOM

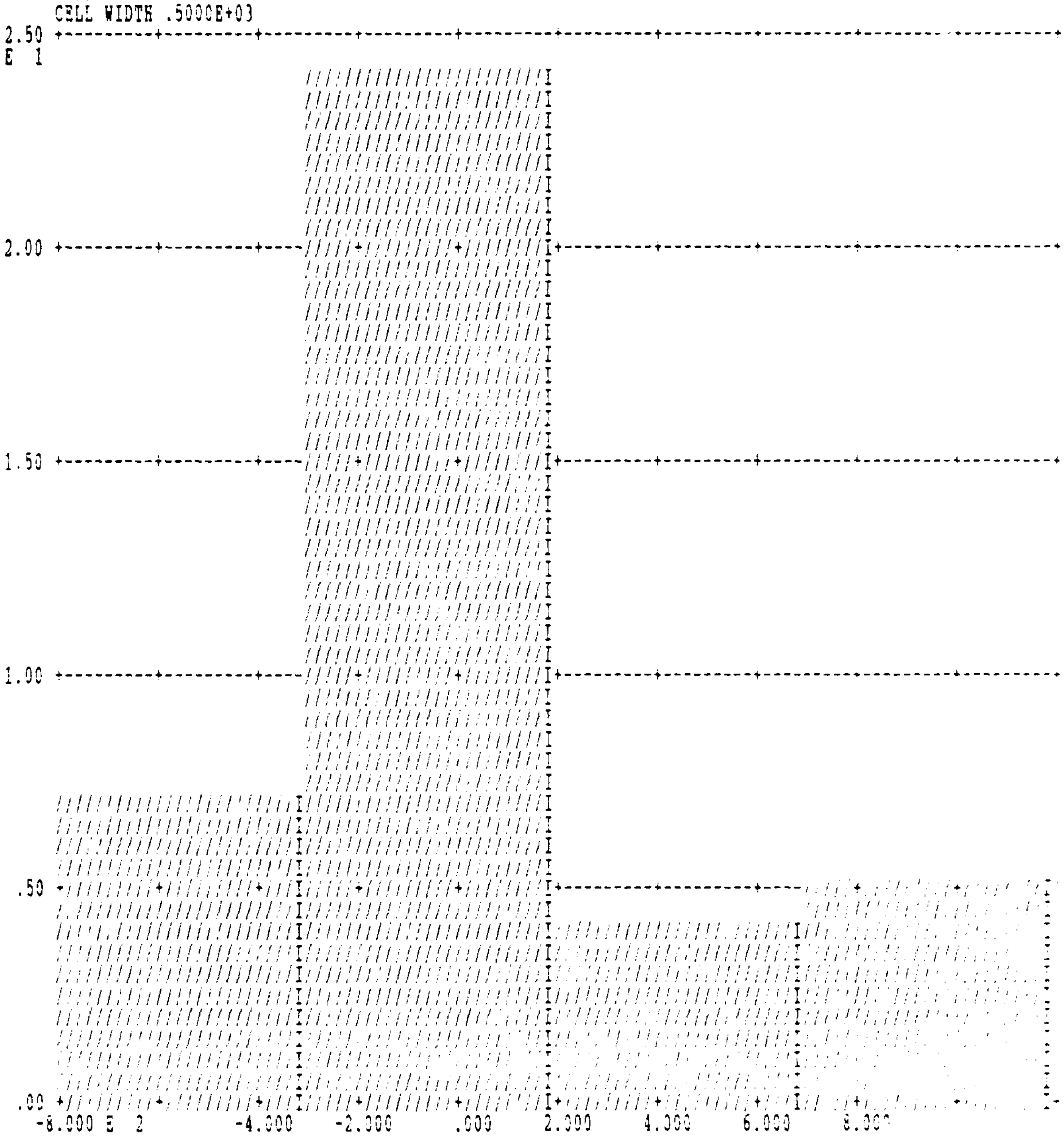
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to PACAF
GRAPH OF OBSERVED SERIES ACF



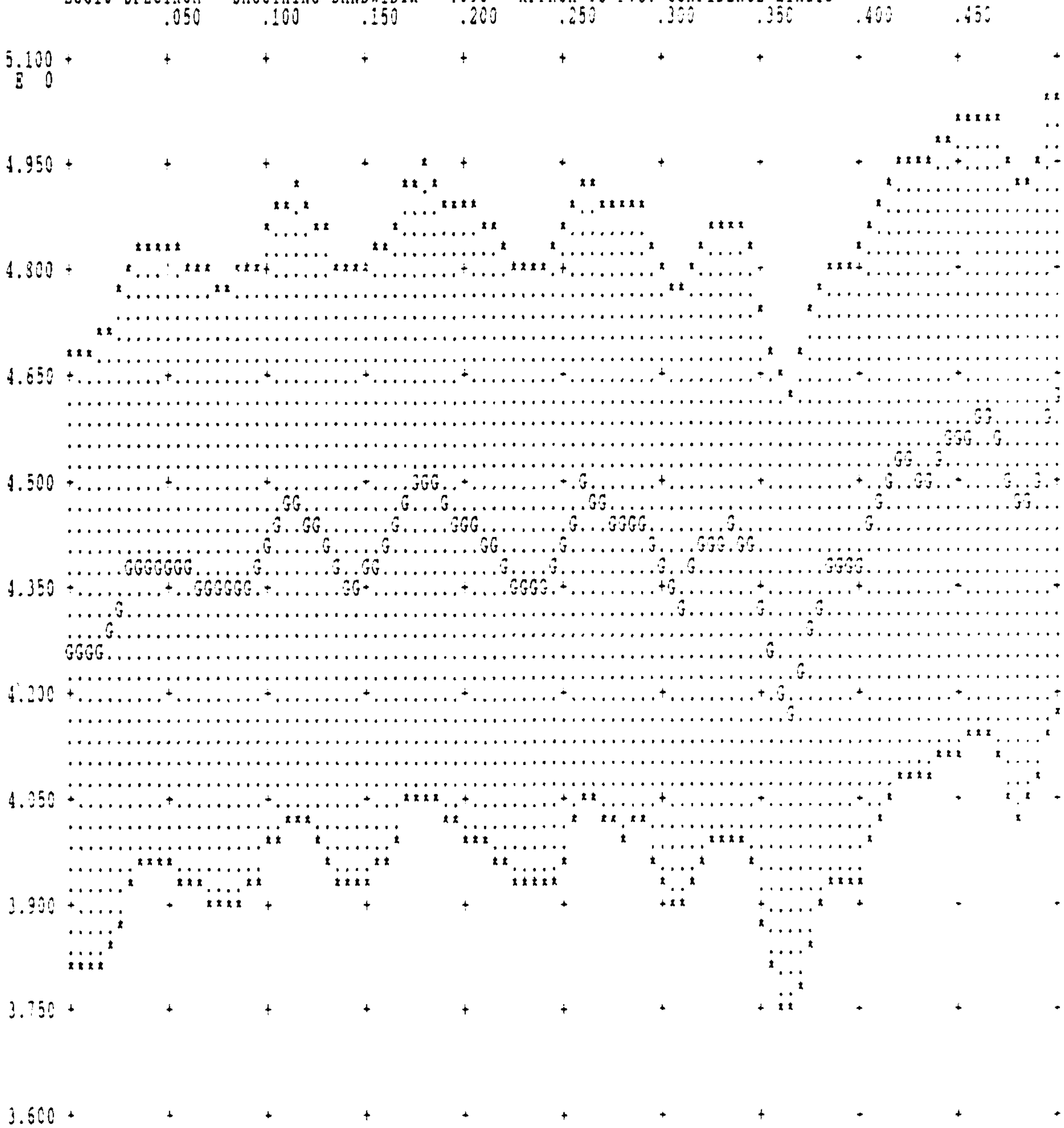
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to PACAF
CUMULATIVE PERIODOGRAM .1 PROBABILITY LIMITS



THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MAC to PACAF
HISTOGRAM
CELL WIDTH .5000E+03



PREWHITENED SDT Tonnage Shipped by MAC to PACAF
LOG10 SPECTRUM SMOOTHING BANDWIDTH = .093 APPROX 95 P.C. CONFIDENCE LIMITS



TIME SERIES FORECASTING FOR SDT Tonnage Shipped by MAC to PACAF

****

DATA - Z = SDT Tonnage Shipped by MAC to PACAF 40 OBSERVATIONS

DIFFERENCING ON Z - NONE

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE
1	MEAN	0	.60644E+04
2	MOVING AVERAGE 1	1	-.40823E+00

****

NUMBER OF TIME ORIGINS FOR FORECASTS = 1

NUMBER OF FORECASTS AT EACH TIME ORIGIN = 6

FORECAST TIME ORIGINS ARE T = 40

SDT Tonnage Shipped by MAC to PACAF FORECASTS BASE PERIOD 40 WITH 95 PER CENT CONFIDENCE LIMITS

PERIODS AHEAD	LO. CONF. LIMIT	FORECAST	UP. CONF. LIMIT
1	.5129552E+04	.5909111E+04	.6688671E+04
2	.5222385E+04	.6064400E+04	.6906415E+04
3	.5222385E+04	.6064400E+04	.6906415E+04
4	.5222385E+04	.6064400E+04	.6906415E+04
5	.5222385E+04	.6064400E+04	.6906415E+04
6	.5222385E+04	.6064400E+04	.6906415E+04

SUMMARY OF SDT Tonnage Shipped by MSC to PACAF

****

DATA - Z = SDT Tonnage Shipped by MSC to PACAF — 40 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.26403E+00	-.59377E+00	.66710E-01
2	MOVING AVERAGE 1	3	.74567E-01	-.26620E+00	.41533E+00
3	MOVING AVERAGE 1	4	-.18636E+00	-.53064E+00	.15993E+00

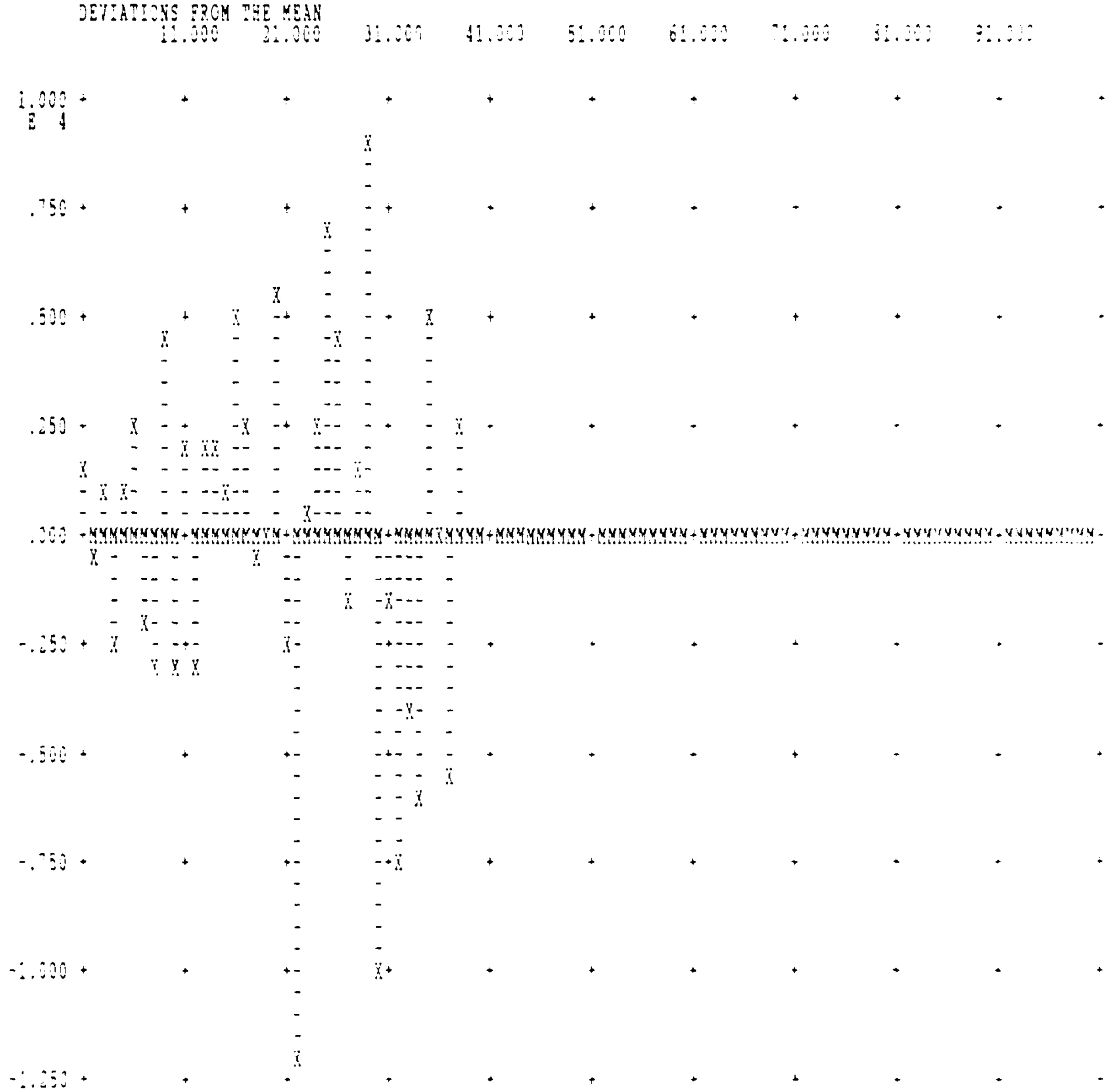
****

OTHER INFORMATION AND RESULTS

****

RESIDUAL SUM OF SQUARES	.73576E+09	35 D.F.	RESIDUAL MEAN SQUARE	.21022E+08
NUMBER OF RESIDUALS	38		RESIDUAL STANDARD ERROR	.45849E+04

THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to PACAF
OBSERVED SERIES
DEVIATIONS FROM THE MEAN



AUTOCORRELATION FUNCTION

DATA - THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to PACAF 40 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

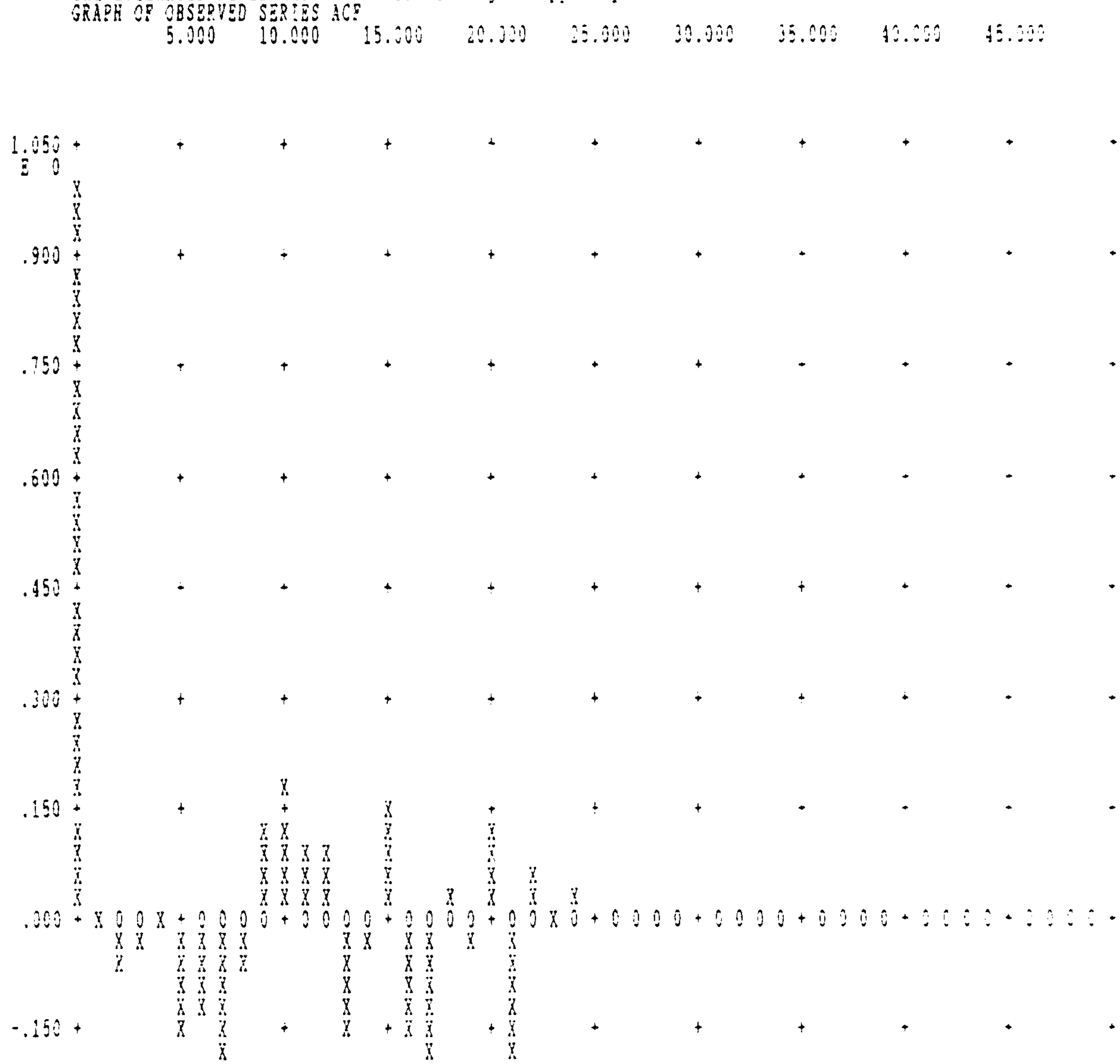
ORIGINAL SERIES
MEAN OF THE SERIES = .17220E+03
ST. DEV. OF SERIES = .44559E-04
NUMBER OF OBSERVATIONS = 38

1- 12	-.01	-.05	-.02	.01	-.15	-.12	-.19	-.06	.13	.13	[illegible]	[illegible]
ST.E.	.16	.16	.16	.16	.16	.17	.17	.17	.17	.18	[illegible]	[illegible]
13- 24	-.16	-.04	.15	-.15	-.13	.02	-.03	.11	-.13	.07	[illegible]	.02
ST.E.	.18	.19	.19	.19	.19	.20	.20	.20	.20	.20	[illegible]	[illegible]

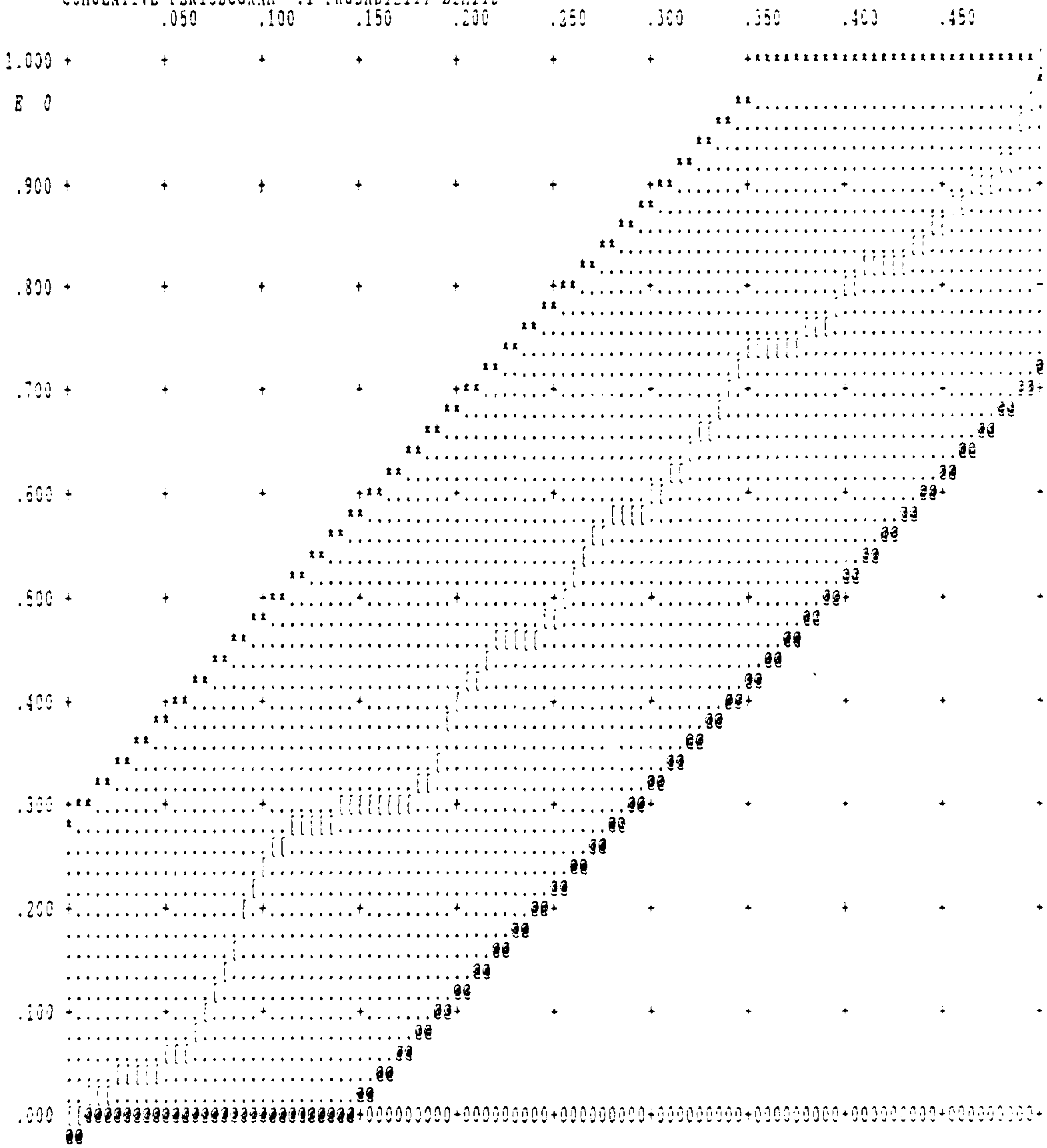
MEAN DIVIDED BY ST. ERROR = .23823E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .11469E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 21 DEGREES OF FREEDOM

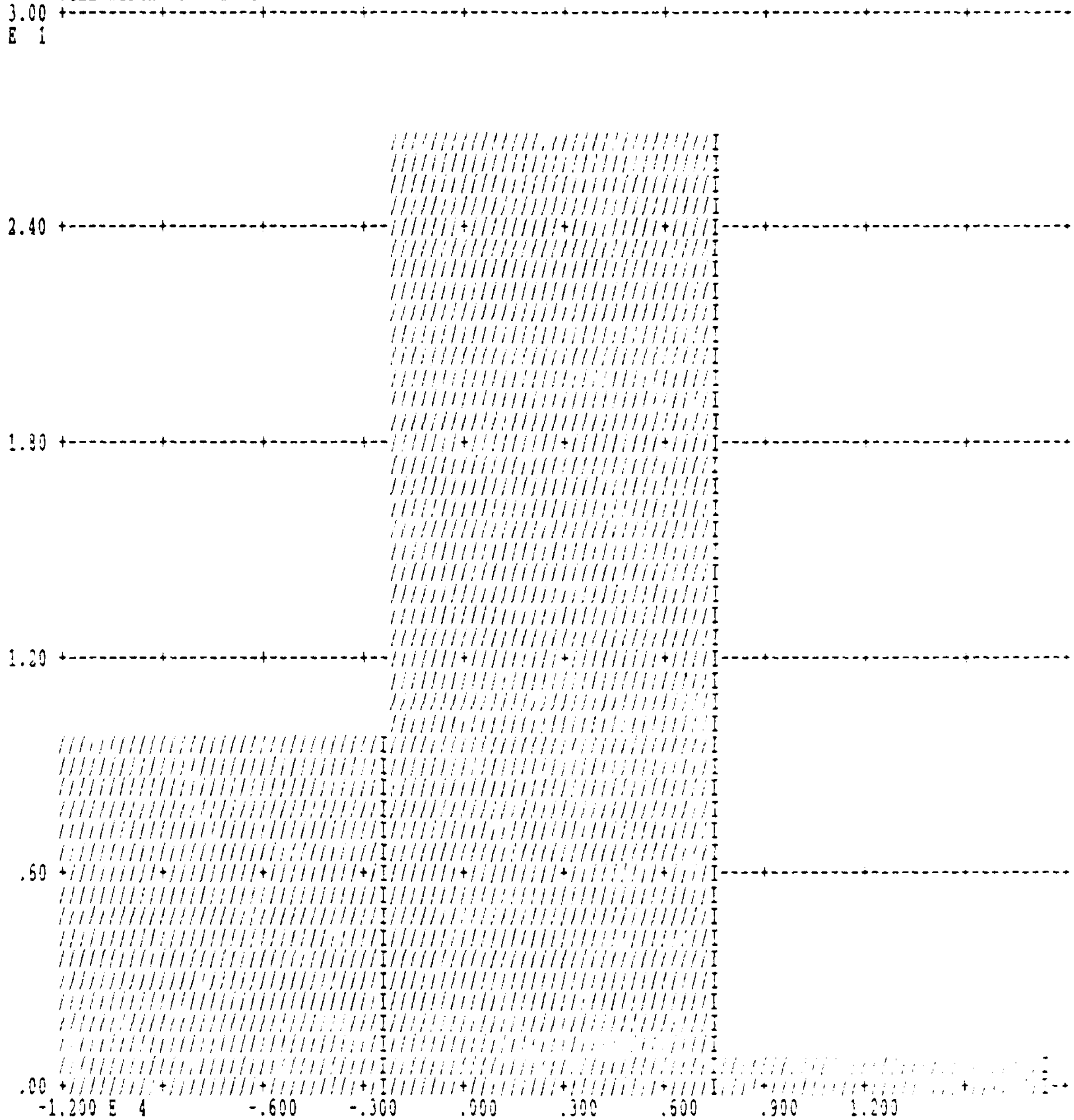
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to PACAF
GRAPH OF OBSERVED SERIES ACF



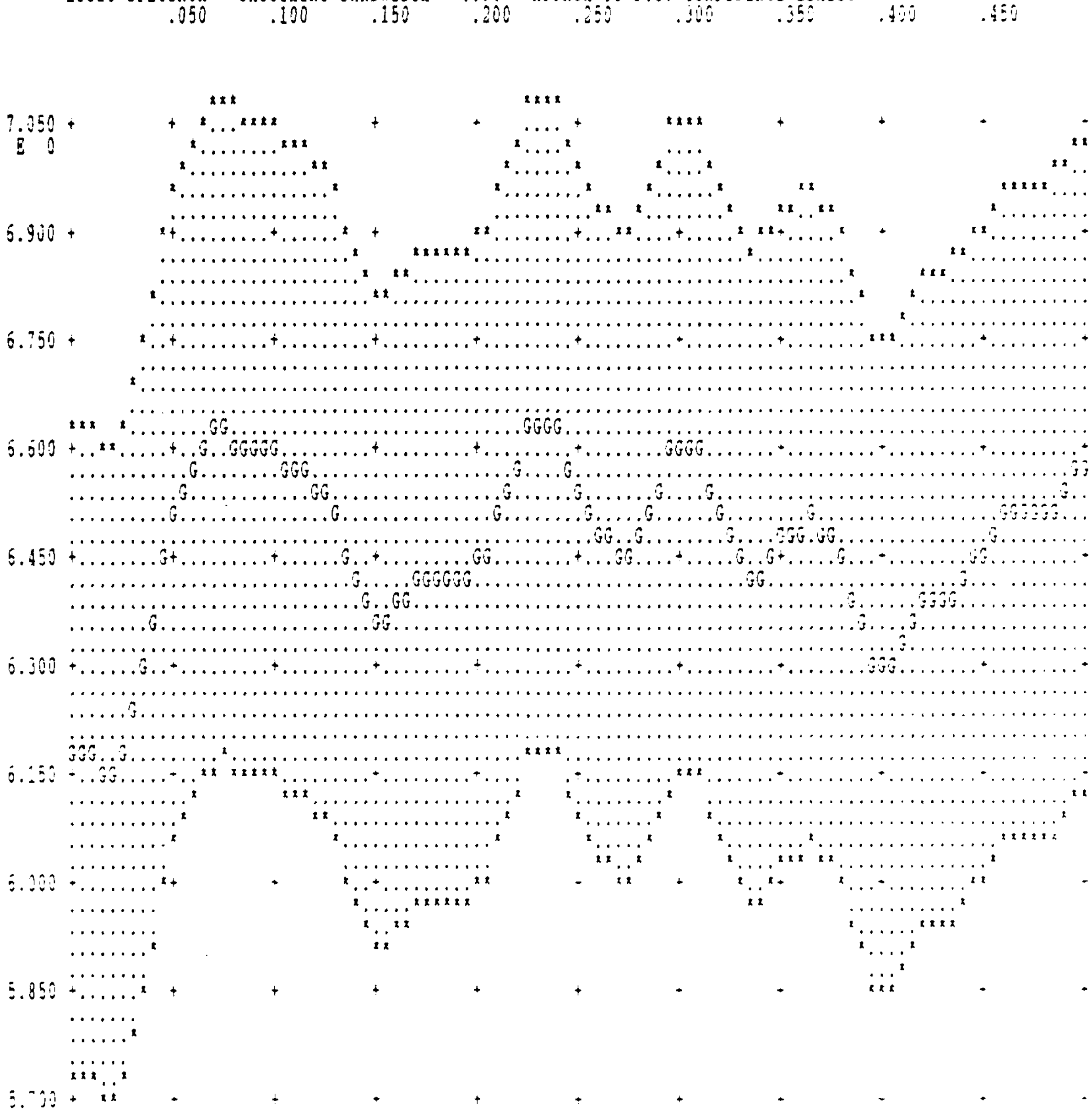
THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to PACAF
CUMULATIVE PERIODOGRAM .1 PROBABILITY LIMITS



THE ESTIMATED RESIDUALS -- SDT Tonnage Shipped by MSC to PACAF
HISTOGRAM
CELL WIDTH .9900E+04



PREWHITENED SDT Tonnage Shipped by MSC to PACAF
LOG10 SPECTRUM SMOOTHING BANDWIDTH = .098 APPROX 95 P.C. CONFIDENCE LIMITS



TIME SERIES FORECASTING FOR SDT Tonnage Shipped by MSC to PACAF

****

DATA - Z = SDT Tonnage Shipped by MSC to PACAF 40 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE
1	AUTOREGRESSIVE 1	1	-.26403E+00
2	MOVING AVERAGE 1	3	.74567E-01
3	MOVING AVERAGE 1	4	-.18636E+00

****

NUMBER OF TIME ORIGINS FOR FORECASTS = 1

NUMBER OF FORECASTS AT EACH TIME ORIGIN = 6

FORECAST TIME ORIGINS ARE T = 40

SDT Tonnage Shipped by MSC to PACAF FORECASTS BASE PERIOD 40 WITH 95 PER CENT CONFIDENCE LIMITS

PERIODS AHEAD	LO. CONF. LIMIT	FORECAST	UP. CONF. LIMIT
1	.2801793E+05	.3700442E+05	.4599091E+05
2	.2622246E+05	.3738038E+05	.4853830E+05
3	.2279647E+05	.3609761E+05	.4939875E+05
4	.2217659E+05	.3693942E+05	.5170225E+05
5	.1978104E+05	.3671716E+05	.5365329E+05
6	.1813002E+05	.3677584E+05	.5542167E+05

Bibliography

1. Abell, Joseph A. Evaluation of Bivariate (Linear) Regression for Use as Tonnage Forecasting Model. Unpublished report. Directorate of Material Requirements, DCS Logistics Operations, HQ AFLC/LORET, Wright-Patterson AFB OH, March 1982.

2. Christensen, Lieutenant Colonel Bruce P. "Forecasting," Military Logistics. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, May 1988.

3. -----. LOGM 630 class lectures in Forecasting Management. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, 27 March to 2 June 1989.

4. Cook, Thomas D. and Donald T. Campbell. Quasi-Experimentation: Design & Analysis Issues for Field Settings. Boston: Houghton Mifflin Company, 1979.

5. Department of Defense. Glossary of Terms Used in the Areas of Financial, Supply, and Installation Management. DOD Instruction 5000.8. Washington: Government Printing Office, 15 June 1961.

6. Emory, C. William. Business Research Methods (Third Edition). Homewood IL: Richard D. Irwin Incorporated, 1985.

7. Foster, Newton W. A Working Paper on Second Destination Transportation (SDT) Forecasting. Unpublished report. Directorate of Management Sciences, DCS Plans and Programs, HQ AFLC,XRS, Wright-Patterson AFB OH, July 1977.

8. Grayson, Major John. An Analysis of Budgeting for Second Destination Transportation. Unpublished report. Air Command and Staff College, Maxwell AFB AL, May 1977.

9. Hoff, John C. A Practical Guide to BOX-JENKINS Forecasting. Belmont CA: Lifetime Learning Publications, 1983.

10. Lamb, Captain Christopher J. and Captain Joseph B. Sarnacki. Formulation of a Model to Predict Second Destination Transportation Tonnage Estimates for Future Budget Requirements. MS thesis, LSSR 21-78B. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1978 (AD-A060490).

11. Makridakis, Spyros and Steven C. Wheelwright. Interactive Forecasting: Univariate and Multivariate Methods (Second Edition). San Francisco: Holden-Day Incorporated, 1978.

12. Menker, George T., Financial Officer, Budget and Requirements Division, Directorate of Programs and Resources, DCS Distribution, HQ AFLC/DSXR, Wright-Patterson AFB OH. Personal interviews conducted intermittently from 17 January 1989 to 2 March 1989.

13. -----. "Transportation Budget." Address to AFIT students. Air Force Institute of Technology (AU), Wright-Patterson AFB OH, January 1989.

14. Narragon, E. A. and J. M. Neil. Second Destination Transportation: Phase 2. Logistics Management Institute Task 75-4. Washington: LMI, January 1976 (AD-A022602).

15. Neter, John and William Wasserman. Applied Linear Statistical Models: Regression, Analysis of Variance, and Experimental Designs. Homewood IL: Richard D. Irwin Incorporated, 1974.

16. Ott, Lyman. An Introduction to Statistical Methods and Data Analysis (Third Edition). Boston: PWS-Kent Publishing Company, 1988.

17. Pindyck, Robert S. and Daniel L. Rubinfeld. Econometric Models and Economic Forecasts (Second Edition). New York: McGraw-Hill Book Company, 1981.

18. Reusche, Lieutenant Colonel Michael, Staff Transportation Officer, Plans and Programs Division, Directorate of Transportation, HQ USAF/LETX, Washington DC. Telephone interview, 17 January 1989.

19. Schonberger, Richard J. and Edward M. Knod, Jr. Operations Management: Serving the Customer (Third Edition). Plano TX: Business Publications Incorporated, 1988.

20. "Tonnage," Encyclopedia Britannica, 11: 838. Chicago: Encyclopedia Britannica Incorporated, 1985.

Vita

Captain Stephen L. Strom [redacted] He graduated from D. W. Daniel [redacted] Captain Strom attended Clemson University from which he received the degree of Bachelor of Science in Civil Engineering in 1985. He was commissioned through the ROTC program on 10 August 1985 and was called on active duty in October 1985. He completed the basic transportation officer course at Sheppard AFB, Texas, and was subsequently assigned to the 410th Transportation Squadron, K. I. Sawyer AFB, Michigan. While assigned to the 410th Transportation Squadron, Captain Strom served as the Transportation Plans and Programs Officer and the Vehicle Operations Officer.

[redacted]

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1a. REPORT SECURITY CLASSIFICATION UNCLASSIFIED	1b. RESTRICTIVE MARKINGS
2a. SECURITY CLASSIFICATION AUTHORITY	3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution unlimited
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER(S) AFIT/GLM/LSM/89S-59	5. MONITORING ORGANIZATION REPORT NUMBER(S)
6a. NAME OF PERFORMING ORGANIZATION School of Systems and Logistics; 6b. OFFICE SYMBOL (If applicable) AFIT/LSM	7a. NAME OF MONITORING ORGANIZATION
6c. ADDRESS (City, State, and ZIP Code) Air Force Institute of Technology Wright-Patterson AFB OH 45433-6583	7b. ADDRESS (City, State, and ZIP Code)
8a. NAME OF FUNDING / SPONSORING ORGANIZATION; 8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER
8c. ADDRESS (City, State, and ZIP Code)	10. SOURCE OF FUNDING NUMBERS: PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO / WORK UNIT ACCESSION NO.

11. TITLE (Include Security Classification)
AN ANALYSIS OF THE AIR FORCE LOGISTICS COMMAND (AFLC) FORECASTING METHOD FOR PREDICTING SECOND DESTINATION TRANSPORTATION (SDT)

12. PERSONAL AUTHOR(S)
Stephen L. Strom, B.S., Capt , USAF

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
MS Thesis	FROM ______ TO ______	1989 September	161

16. SUPPLEMENTARY NOTATION

17. COSATI CODES FIELD	GROUP	SUB-GROUP
12	03	

18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
Forecasting, Second Destination Transportation, Transportation, Military Transportation

19 ABSTRACT (Continue on reverse if necessary and identify by block number)

Thesis Advisor: Robert E. Trempe, Lt Col, USAF
Instructor in Logistics Management
Department of Logistics Management

Approved for public release: IAW AFR 190-1.

Larry W. Emmelhainz

LARRY W. EMMELHAINZ, Lt Col, USAF 11 Oct 89
Director of Research and Consultation
Air Force Institute of Technology (AU)
Wright-Patterson AFB OH 45433-6583

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED
22a. NAME OF RESPONSIBLE INDIVIDUAL Robert E. Trempe, Inst. in Logistics Mang.	22b. TELEPHONE (Include Area Code) (513) 255-4149; 22c. OFFICE SYMBOL LSM

DD Form 1473, JUN 86 Previous editions are obsolete.

SECURITY CLASSIFICATION OF THIS PAGE
UNCLASSIFIED

This research was conducted to analyze the Air Force Logistics Command (AFLC) forecasting method for predicting Second Destination Transportation (SDT) tonnage with the regional flying hour program. This thesis had two main objectives: (1) validate the current forecasting method used for computing tonnage estimates to derive SDT budget requests, and (2) if the current method's validity was not supported, develop a new forecasting model, using the same input data, that would produce more accurate and reliable tonnage estimates.

Analyzing graphs of the four different data sets researched in this thesis and then conducting a statistical test on the flying hour parameter for each set, it was determined that the current method employed to forecast SDT tonnage was statistically invalid for two of the four sets. This determination was made due to the fact that the flying hour parameter changed during the iterative regression process used. This change implied that SDT tonnage and flying hours were not linearly related.

Box-Jenkins (BJ) time series forecasting models for each data set were built and provided accurate and valid forecasts. For the MAC SDT time series, the BJ models were more accurate than the current method. The BJ models for the MSC SDT time series, although marginally less accurate than the current method, were valid, whereas the current method for these two series was statistically invalid.

This research emphasized the need for an accurate model and an increase in the size of the data base used for forecasting. It was also noted that forecasting SDT tonnage requires continual analysis and updating to ensure the model being used is appropriate for the data being forecasted. Finally, in statistically invalidating the current model, this research has caused an immediate need for an accurate and valid model. Further research, particularly with econometric models, would prove beneficial.